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Documenting Meter Tests at the Iowa Energy Center

Element 5
Project 2.2
Task 3

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High Performance Commercial Building Systems
PIER Program

Element 5: Integrated Commissioning and Diagnostics

Task 2.2.3 Develop and Test Hardware and Software for High Information Content Electrical Load Monitoring

Report: Documenting Meter Tests During Year One

by

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1 Introduction

Information about electrical loads in a building is of value to many individuals and organizations: facility managers would like to minimize operating costs and the costs and down-time associated with repairs, electric utilities and service providers need accurate load models to most economically generate, transmit and distribute power, and energy service companies and building owners would like inexpensive means to verify savings from energy-efficiency improvements. Electrical-power information can also be used for power-quality monitoring, load analysis, and fault detection and diagnosis.

The current report presents the field-test results of the steady-state non-intrusive load monitoring (SS-NILM) system developed at M.I.T., and its suitability to load monitoring and fault detection and diagnosis in a small commercial building, specifically a KFC Restaurant in Norwell Massachusetts. The results from the NILM system were validated using an independent and "traditional" multi-channel end-use power-metering system installed at the site.

The organization of this report is as follows:

First a general description of the NILM system developed at M.I.T., hardware and software, is given in chapter two, followed by a description of the test sites selected for this project in chapter three. The site description includes the equipment connected to the electrical panel monitored by the NILM system as well the parallel power-metering system, installed to validate the results obtained from the NILM system.

A discussion and comparison of the results obtained from the NILM and the parallel monitoring systems, as well as the modifications made to the NILM software components based on these results are presented in chapter four of the report.

Conclusions and recommendations for possible future work are discussed and presented in the final chapter of the report.

It should be noted that the proposed deliverable for this task was intended to focus on tests performed at the Iowa Energy Center's Energy Resource Station, at Des Moines Area Community College in Ankany, Iowa. This same test site has been used for complementary tests performed for the California Energy Commission under the prime contract held by Architectural Energy Corporation. The emphasis of the AEC work has been on detection of on/off switching events and on detection of faults. The emphasis of the LBNL work has been on estimation of energy consumption. The Principal Investigator has elected to package all work at the Iowa test site in the reports prepared for AEC. A copy of the final report will also be sent to LBNL. This report includes work on estimation of energy consumption. As noted above, the report for LBNL focuses on analysis of data from extensive tests performed at a fast-food restaurant in Massachusetts. The analysis has concentrated on energy estimation and not fault detection and the site has a richer set of equipment than does the site in Iowa. Code developed for the restaurant will be used in California buildings, as a means of not only detecting loads but also automatically classifying them and automatically estimating component-level energy consumption.

2 Non Intrusive Load Monitoring System

Non-intrusive load monitoring (NILM) systems were, and are being, developed to simplify the monitoring of electric loads or appliances on a building electrical system or subsystem by providing system information based on electric measurements taken at a single point in the circuit, instead of measurements at each load of interest [1,2] (Figure 2-1).

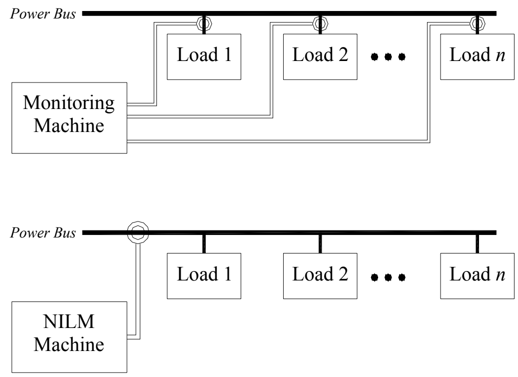


Figure 2-1 *Conventional vs. Non Intrusive Monitoring Systems.*

The single-point monitoring of the NILM system offers several advantages and disadvantages over traditional monitoring systems. Among the advantages are the reduced number of components in the monitoring system (lower equipment and installation costs), and the system flexibility and load monitoring capacity: the number of loads a NILM system could monitor is not limited by the physical constraints of the system (i.e. the number of available monitoring channels). Among the disadvantages is the increased complexity and computational cost of the system software and inaccuracies in resolving individual loads.

2.1 NILM Hardware Description

The current NILM hardware system developed at MIT, and the one used at the test site described later in this report, is based on a personal computer (200MHz Intel compatible processor with mmx, 64MB of RAM and 6GB Hard Drive) running *Linux* as the operating system. The computer contains an analog to digital converter (ADC) card for data collection, and an Ethernet network card for communications. Figure 2-2 depicts a block diagram of the hardware used in the NILM system deployed at the test site.

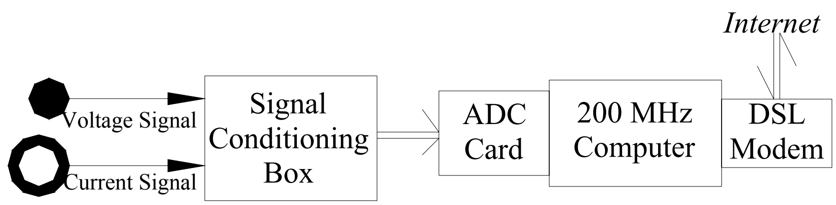


Figure 2-2 *NILM System Hardware Block Diagram.*

The ADC card samples voltage and current signals at a sampling rate of approximately 8kHz. The digitized signals are then processed by the computer and stored on the internal hard drive. A Signal Conditioning box is used to interface the voltage and current sensor signals with the ADC card. Current sensors are closed coil current transducers installed around the monitored cables, while the voltage sensors are simple voltage taps connected to the monitored circuit. Although the ADC has multiple input channels for monitoring multiple circuits (i.e. three-phase circuits), the current hardware and software implementation of the NILM can only monitor a single circuit phase at any given time. This shortcoming is currently being addressed, and simultaneous monitoring of the three phases of a commercial electric installation should soon be possible.

The NILM computer is accessible through the Internet. The current configuration allows for remote NILM software maintenance and system control. Also, the stored data in the hard drive are remotely retrieved and analyzed.

2.2 General NILM Software Description

The NILM approach is based on the idea that a power signal can be decomposed by recognizing the transients that occur when a given load is switched on or off. There are three key NILM tasks: detection, load classification, and estimation of energy consumption.

NILM system can be divided in two main approaches: steady state and transient approaches. In the steady-state approach, load events are classified based on their steady state characteristics due to a state change (i.e. turn on or off). The transient approach relies on the shape and structure of the transitions between steady states to classify events. The NILM system used for this project is based on the steady state approach for detection and classification of events.

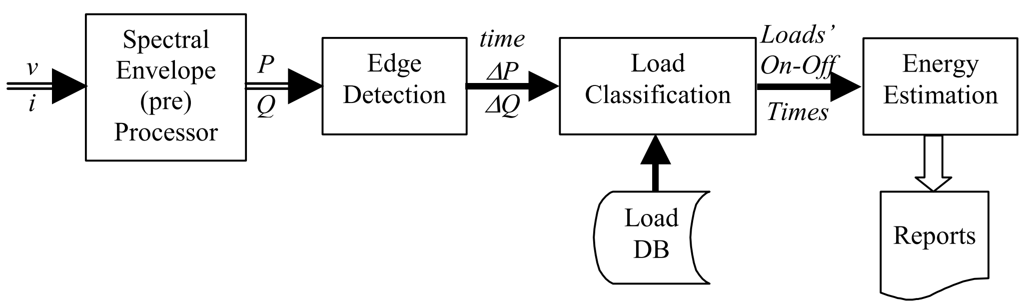


Figure 2-3 *NILM Software Architecture Block Diagram.*

The software used to implement the NILM reads the voltage and current used by the loads on the monitored circuit, and estimates the energy consumption of the individual loads based on the detected turn-on and turn-off events. Figure 2-3 shows a block diagram of the general NILM software architecture used. Four modules are used, which perform the main phases of the steady-state NILM algorithm: spectral envelope preprocessor, edge (event) detection, event (load) classification, and energy consumption estimation. In addition a fifth module is provided to generate reports with the information generated from the NILM main modules.

<u>Spectral Envelope Preprocessor</u> computes the real and reactive power used by the loads from the sampled voltage and current waveforms. Power is the mean of the instantaneous power sampled by the ADC card. The algorithm uses the spectral envelope estimator developed by Leeb et al. in [3,4]. Spectral envelopes are the short-time averages corresponding to the time-local content of a waveform.

<u>Edge Detection</u> identifies changes in steady-state power levels. If a detected change is above a previously defined threshold, an event is defined. The associated real and reactive power changes together with the time of occurrence are stored. The power change detection is performed using the generalized likelihood ratio (GLR) algorithm developed by Luo et al. [17]. The GLR is a statistical algorithm used to detect changes in mean values in a data series.

<u>Load Classification</u> is made by associating the change of real and reactive power during an event to the turn on or off of a load. A database containing change of power information for the loads present on the monitored circuit, and a history of load states are used to match the recorded events to the loads.

<u>Energy Consumption</u> is estimated using the information obtained from the load-classification module on the loads turn on and off times, and the load average power consumption from the load database.

In the current NILM implementation, the first software module (spectral envelope preprocessor) is running in the Linux box at the monitored site. The remaining modules are implemented offline. The real and reactive power data series for a given period of time are downloaded through the internet and analyzed off line using the programs developed in Matlab®.

3 Test Buildings

3.1 KFC Restaurant

The KFC restaurant in Norwell Massachusetts (11 Washington St, Norwell MA 02061) was chosen as one of the test sites for the MIT-developed NILM system. This location was chosen because of its proximity to MIT and because it was already instrumented because it included an automation system of interest in another research project.

The building electrical system is a commercial three-phase 208/230volts system. It contains a main distribution panel (MDP) rated at 800 amps, and four distribution panels connected to the main panel, each rated at 225 amps. (Figure 3-1)

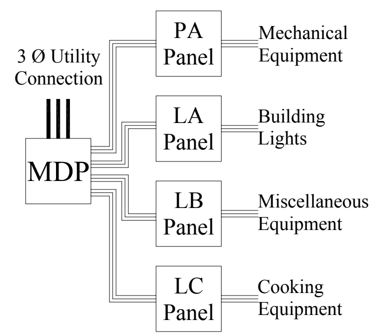


Figure 3-1 *Building Electrical Distribution System.*

The electrical loads in the building are distributed among these four panels according to their type. The four types of loads in the building are mechanical equipment, building lights, cooking equipment, and miscellaneous office and point-of-sale equipment.

Only one phase (phase A) of the mechanical equipment panel was monitored, using both the NILM system described previously and a commercially available (Synergistic C180) power metering and logging system.

3.1.1 Mechanical Equipment Description

As mentioned previously, most of the mechanical equipment in the building is connected to a single electric distribution panel (PA Panel). The equipment connected to this panel includes two rooftop HVAC units, two exhaust fans, one make-up fan, two walk-in refrigeration units (a cooler and a freezer), and an ice-making machine. In addition to the mechanical equipment, the PA panel also serves an electric convection oven, freezer and cooler accessories, and two water heaters. Table 1 summarizes the equipment connected to the PA panel.

Table 1 *Equipment connected to PA panel.*

Equipment	Voltage (V)	Max. Current (A)	Phases	Max. Power (kW)	Comments
Kitchen HVAC	208/230	47.3	3	10.8	Two stage roof-top unit. 10-ton capacity. Gas fired heating.
Lobby HVAC	203/230	34.5	3	7.9	Two stage roof-top unit. 7-1/2 ton capacity. Gas fired heating.
Exhaust Hoods	208/230	10	3	2.1	Two fans. 18" impellers, 1hp motors.
Make-up Fan	208/230	5	3	1.2	15"impeller, 1.5hp motor.
Walk-in Cooler	208/230 230	8.8 8.9	3 1	---	Compressor in 3-phase. Fans in 1-phase. Temperature set point: 36°F. Coil defroster is disabled.
Walk-in Freezer	208/230 230	7.9 10.9	3 1	---	Compressor in 3-phase. Fans in 1-phase. Temperature set point: 10°F. Coil defroster on timer.
Ice Machine	208/230	7.5	1 (A-B)	1.7	Uses 6.8kWh per 100lb of ice produced. Capacity: 600lb every 24 hours.
Convection Oven	208/230	21	3	5.6	Thermostat controlled. Turned on and off manually by restaurant staff.
Water Heaters	208/230	29	1 (B-C)		Thermostat controlled
Accessories	120	---	1 (A-N)	0.6	(Always On)

Since only one phase (phase A) of the circuit was monitored by the NILM system, the equipment not connected to this phase (the water heaters) was ignored[1].

3.1.2 Power Sub-metering System

In order to validate the results obtained from the NILM system installed at the test site, a commercially available power metering and logging system was installed at the site to provide sub-metered data (Figure 3-2).

[1] One of the water heaters was originally connected across phases A and B, and introduced high levels of noise into the monitored power signal. In order to clean the monitored signal, it was reconnected across phases B and C.

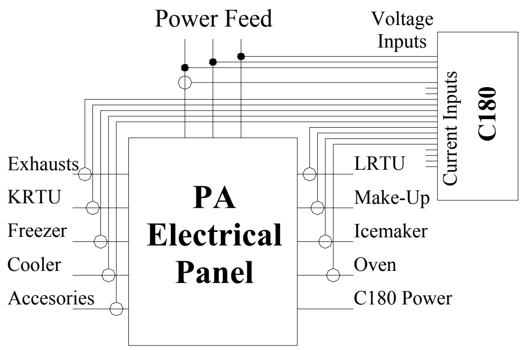


Figure 3-2 *C180 System Connection to Electrical Panel.*

The system selected is a Synergistic® sixteen-channel power meter and logger model C180. The C180 logger collects and stores one-minute averages of the real and apparent power measured on each of the sixteen channels. The C180 data is retrieved using a modem connection and Synergistic's® software running on a personal computer.

Current is measured by the C180 using one split-core current transducer per channel. The transducers are installed around the cable (conductor) leaving each monitored circuit breaker. Three voltage measurements are taken, one for each of the circuit phases using potential-tap breakers (PT-Breaker) connected to the conductors feeding the PA electrical distribution panel. Table 2 shows the sub-metered equipment and the corresponding C180 channel assignments.

Table 2 *Sub-metered Equipment using C180 logger.*

C180 Channel	Monitored Equipment	Comments
0	PA Electrical Panel (A)	Total power used by PA distribution panel.
1	Not connected (B)	Phase A monitored by NILM system. *Phase*
2	*PA Electrical Panel (C)*	*B sensor did not fit inside panel.*
3	Exhaust Hoods	3 phase loads. Only phase A is monitored.
4	Kitchen HVAC	
5	Walk-in Freezer	
6	Walk-in Cooler	
7	Freezer Accessories	1 phase loads connected line A-to-N.
8	Lobby HVAC	3 phase loads. Only line A is monitored.
9	Make-Up Fan	
10	Ice Making Machine	1 phase load connected line-to-line (A-B).
11	Convection Oven	3 phase load. Only line A monitored.
12	*Water Heater*	One phase loads connected line-to-line (B-C).
13	Not Connected	They do not show in data collected by NILM
14	*Water Heater*	system.
15	*Kitchen HVAC*	Phase C

[*]Equipment in *italics* is not monitored by the NILM system.

4 NILM System Results and Sub-metering Data

The following sections present the results obtained from the different NILM system modules and their comparison with the data obtained from the C180 system.

4.1 Performance of Event Detection Module

Event detection module performance was evaluated by making visual comparison of the real power data obtained from the spectral envelope power estimator and the events detected by the detection module.

The event detection module successfully detected **97.4%** of 5420 events over a test period of 7 days. This detection rate was measured as the number of events reported versus the number of actual events observed on the data sequence. Actual event counting on the data sequence was done visually and with the aid of the sub-metered power data obtained from the C180 system.

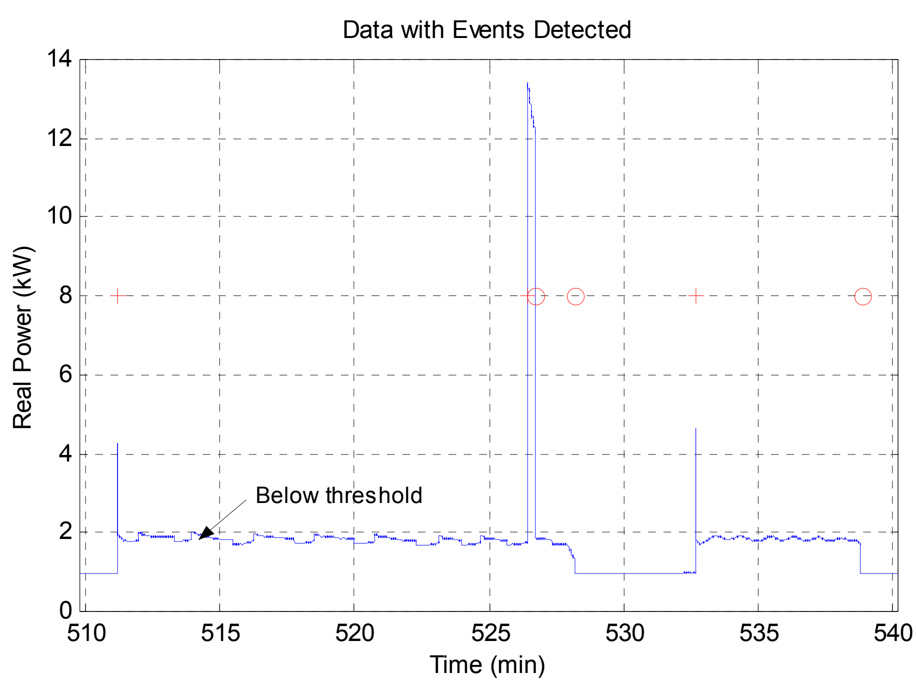


Figure 4-1 *Power data compared to event detection output.*

The detection module ignored events that presented a steady state change below the detection threshold (Figure 4-1). For the current test site, the detection threshold was set at 200 Watts. This threshold was selected by trial and error using the data collected while generating the initial system load database during the initial training period (§4.2.2).

Event detection errors are classified into two main classes: missed event errors and false alarms errors. The first ones occur when the detection module does not report an event, while the second ones occur when an event is reported where there is none.

The overlapping of events causes most of the missed event detection errors. These errors manifest themselves as the total omission of an event by the detection algorithm, or by the assimilation of two distinct events into a single event. Figure 4-2 and Figure 4-3 show examples of missed event errors, while Figure 4-4 shows an example of a false alarm error. The errors generated by the detection module are quantified by type on Table 3.

Table 3 *Detection Errors by Type*

	Detection	False Alarms	Missed Events	
			Separation	Simultaneous
Percentage	97.4 %	0.25 %	1.85 %	0.74 %

Figure 4-2 shows an example in which two events are assimilated into a single one because they occur almost simultaneously. On this example, a cooler shutdown and an oven shutdown occur simultaneously and are reported as a single event.

An example of failure of detection is shown in Figure 4-3. In this example, a turn-on event for the convection oven occurs within a second of a shutdown event for the walk-in freezer. Since the shutdown event is not completely abrupt, as the oven transitions are, the detection algorithm ignores the freezer shutdown event.

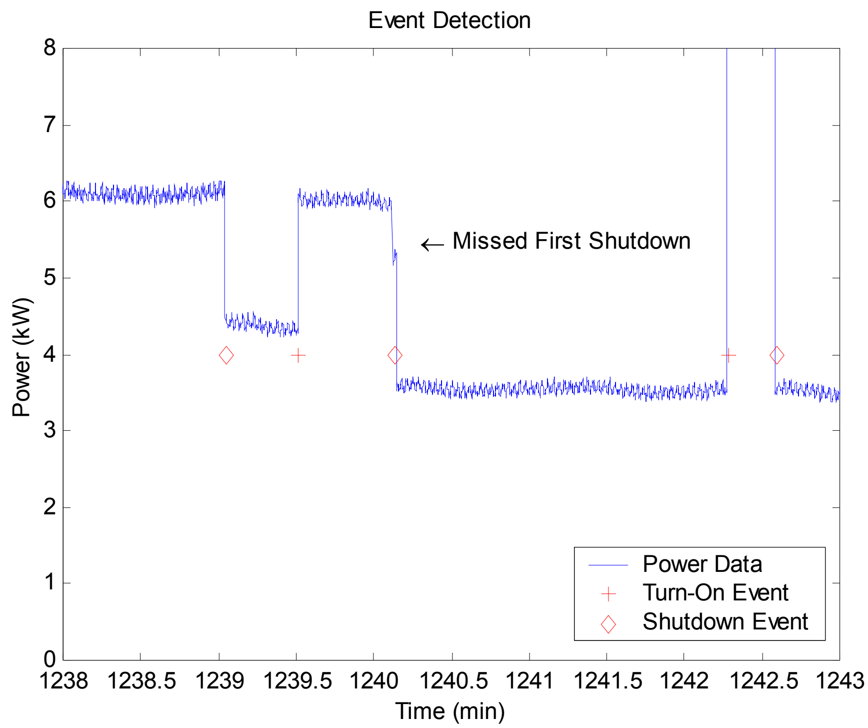


Figure 4-2 *Example of Detection Error because of Simultaneous Events.*

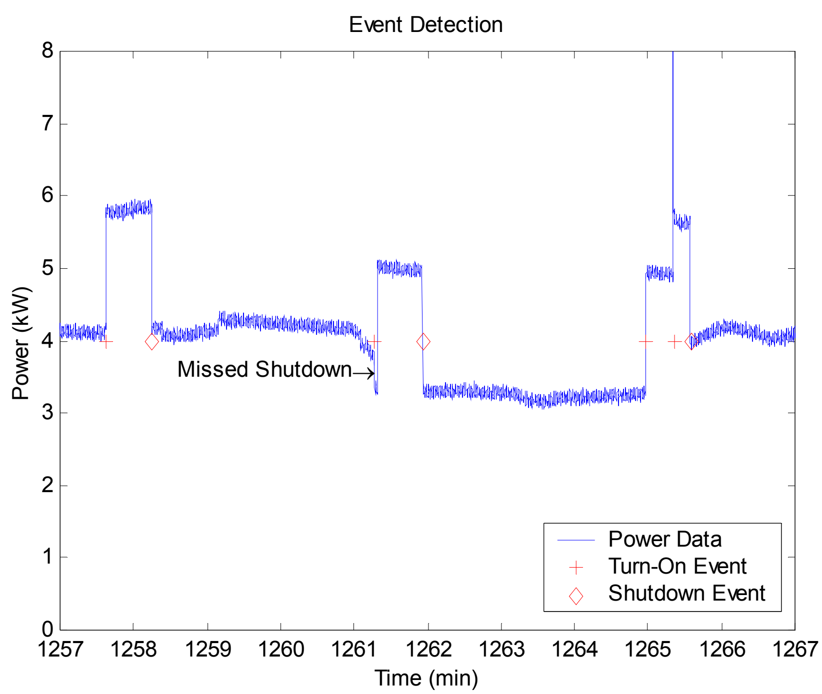


Figure 4-3 *Example of Detection Error because of Event Separation.*

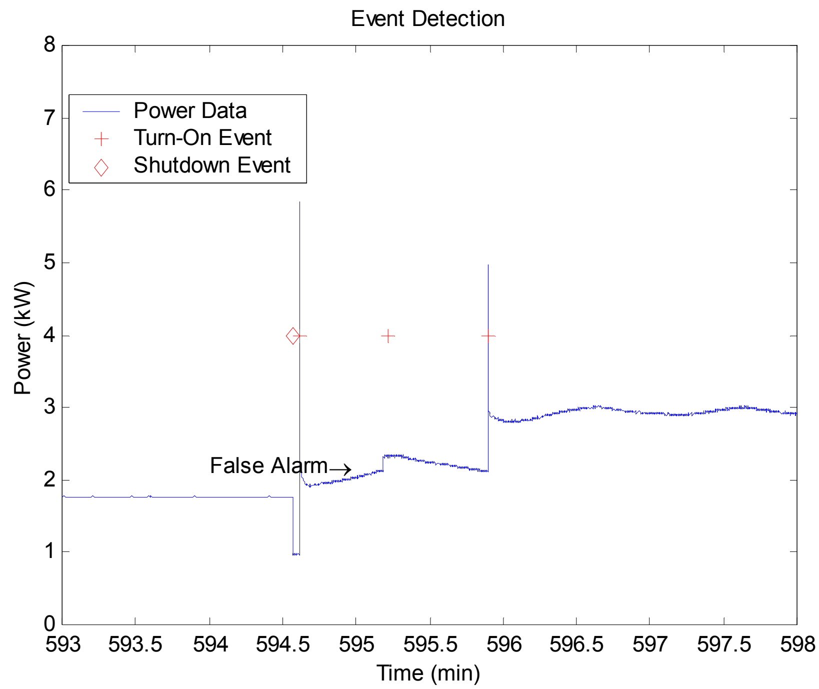


Figure 4-4 *Example of False Alarm Detection Error.*

Figure 4-4 shows an example of a false alarm detection error. In this particular example, an event is reported due to the turn-on of one of the walk-in freezer subcomponents. Luo [18] explains in more detail causes for false alarm detection errors while using the generalized likelihood algorithm for event detection.

4.2 Performance of Event Classification Module

4.2.1 Event Classification and Load Database

Event classification is based on the assumption that it is possible to identify each load[2] (or groups of loads) in the monitored circuit based on the changes of steady state power consumption due to that load's turn-on or shutdown events [1]. An event is classified as one of the known load events[3] in the building or circuit monitored, by comparing its power change in the complex power space (real and reactive power) to the power change of the known events.

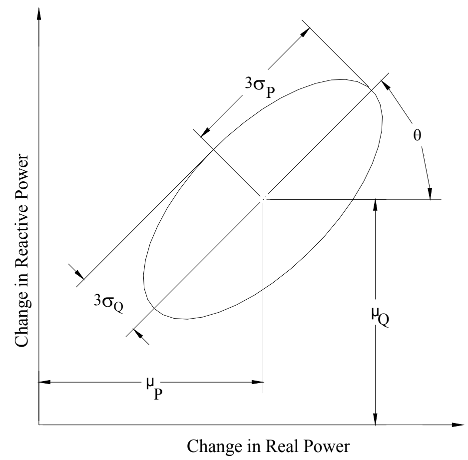


Figure 4-5 *Ellipse Definition based on Event Parameters.*

A database contains information about the loads in the monitored circuit or building in the form of event classes that represent the loads turn-on and shutdown events. An event class can represent a single load, or multiple loads that change state simultaneously. Each event class defines an area in the complex power space (P-Q plane) for each of the load events. These areas are defined using ellipses created from statistical parameters of the turn-on and shutdown events (Figure 4-5).

<u>Database File Format Description</u>

The load-database file contains the information needed to construct the ellipses that describe the clusters for each of the known load events in the monitored site. The file is in ASCII format. Each event class occupies two lines: the first line contains the turn-on event information, while the second line contains the shutdown event information:

---

[2] The term *load* refers to an electric load in the general sense, and not a particular machine or appliance. A machine or appliance in the circuit may contain multiple loads and operational states.
[3] An *event* is the change in steady state power consumption due to the turn-on or shutdown of a load or multiple loads simultaneously.

```
i^th_event_on    μP  μQ  σP  σQ  θ   Avrg_Power  Slaves  Master
i^th_event_off   μP  μQ  σP  σQ  θ  Base_Power Slaves  Master
```

Here, μ_P and μ_Q are the mean real and reactive power change, respectively, due to the load event, σ_P and σ_Q are the standard deviations, and θ is the rotation of the cluster from the horizontal axis.

When the event is due to the state change of a single load *Avrg_Power* is the average power consumption of the load due to the event turn-on. The *Base_Power* value is used to account for the power consumption of loads that do not completely shutdown after the turn-off event (for example, the cooler power consumption was found to never be zero).

When a given event is caused by the simultaneous state change of multiple loads, the *Slaves* value indicates how many loads are involved in the state change. Similarly, the *Master* value indicates if a load event is related to another event in the database.

4.2.2 Initial Load Database Generation

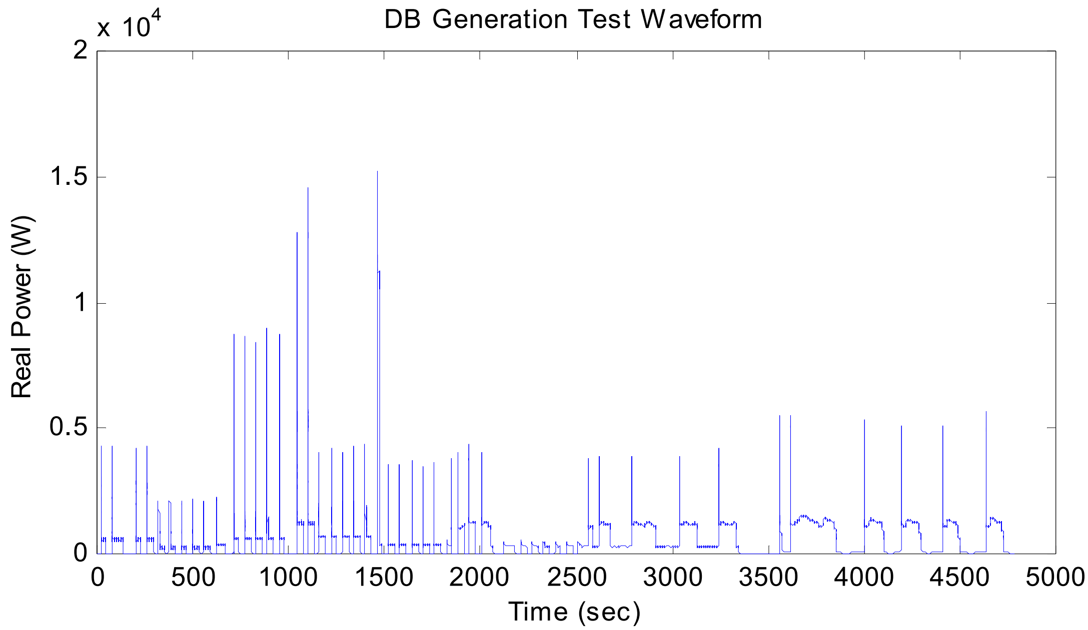
Database generation for load classification is done during a *training* period of the NILM system at the target site. In general, the generation of the initial database can be done either automatically or with an operator intervention [1,6,9,10] using *a priori* information about the loads in the system, or by the analysis of collected data from the site during the training period.

The current NILM implementation needs an operator intervention in order to create the initial load database, and to update it as additional information about the site events is collected. Given that the loads monitored during this project were known, and that some of them were manually controllable, the initial load database used for the load classification module of the NILM program was easily compiled from tests performed at the site.

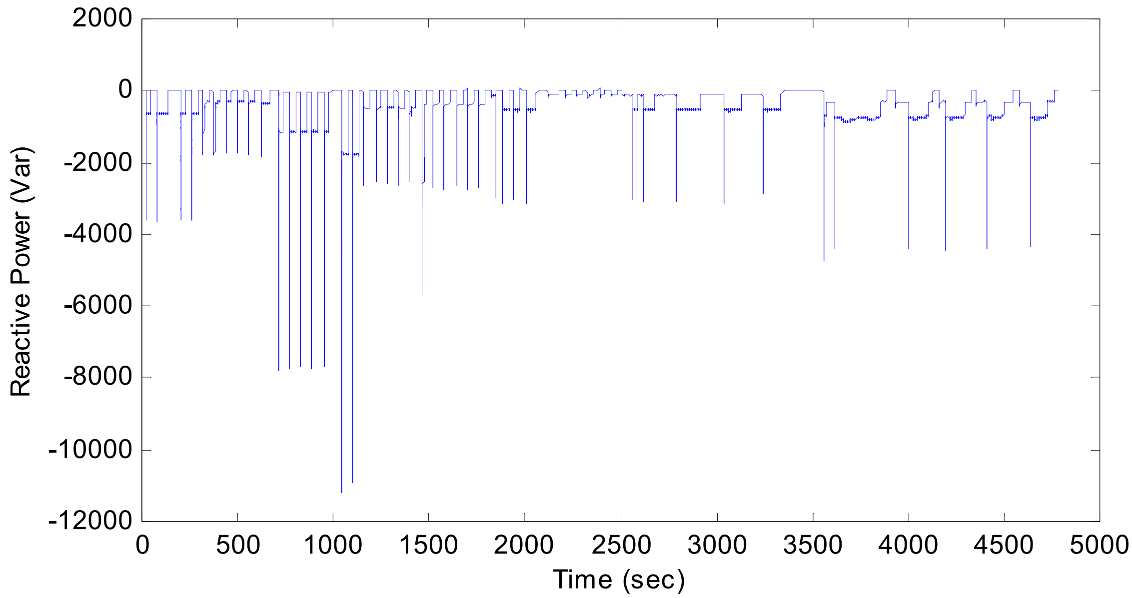
***Table 4** Event Schedule for Initial Database Generation.*

Load Tested	Events Performed	
Exhaust Hood Fans #1 & #2	4 On-Off cycles	
Exhaust Hood Fan #2	5 On-Off cycles	
Exhaust Hood Fan #1	1 On-Off cycle	
Make-Up Fan	5 On-Off cycles	
Make-Up and Exhaust Fans	2 On-Off cycles	
Lobby HVAC (Heating Mode)	5 On-Off cycles	
Kitchen HVAC (Heating Mode)	6 On-Off cycles	
Cooler Evaporator	1 On-Off cycle	
Cooler Evaporator and Condenser	3 On-Off cycles	
Cooler Evaporator	6 On-Off cycles	
Cooler Evaporator	Turn On	
Cooler Condenser	5 On-Off cycles	
Cooler Evaporator	Turn Off	
Freezer Evaporator	Turn On	Repeated 5 times
Freezer Condenser	1 On-Off cycle	
Freezer Evaporator	Turn Off	

A series of tests was performed, in which the different controllable loads in the monitored circuit were individually turned on and off a given number of times at known intervals while power data were being recorded by the NILM system. The power data obtained were then analyzed using the GLR program to obtain the events information. The resulting events' real and reactive power changes were clustered in the complex power space, and the means and standard deviations in the real and reactive domains computed for each of the clusters. Table 4 presents the sequence of events generated for the tests. These tests were performed during the fall. The HVAC units were operating in heating mode and therefore cooling mode data were not obtained.



a) Real Power Waveform



b) Reactive Power Waveform

Figure 4-6 *Database Generation Test Power Waveforms.*

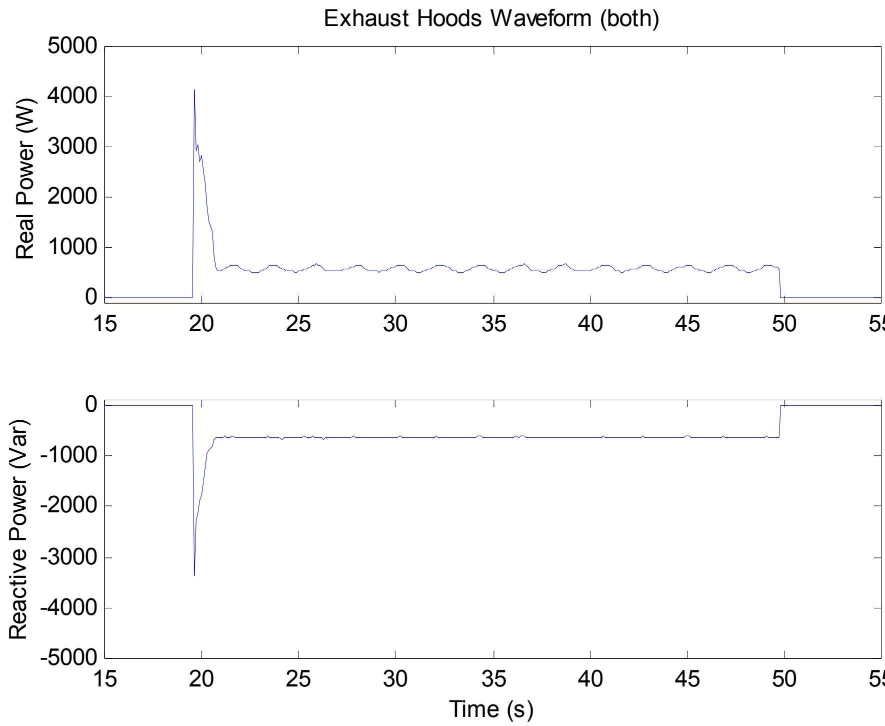
Figure 4-6 (a) and (b) show the real reactive power waveforms obtained while performing the tests described in Table 4. In order to simplify the analysis of the cluster data, the events were divided into six groups: exhaust hood fans, make-up fan, lobby HVAC, kitchen HVAC, walk-in cooler, and walk-in freezer.

Fan Units

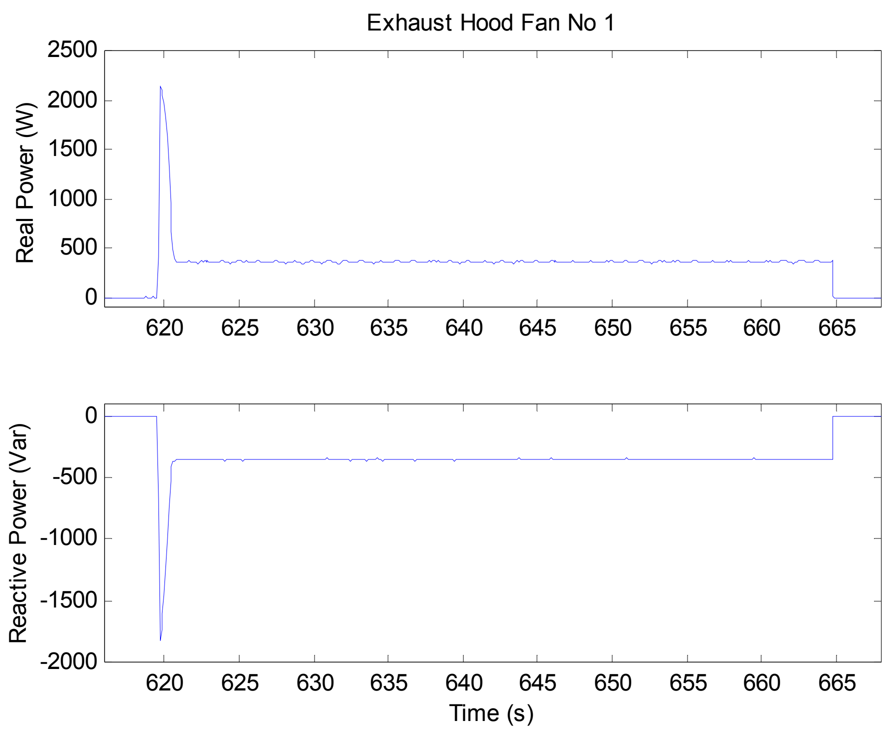
Figure 4-7 and Figure 4-8 show sample power waveforms and the test cluster plots, respectively, for the exhaust hood fans, while Figure 4-9 shows the waveforms for the make-up fan.

Figure 4-10 shows the cluster plots of changes in steady-state power due to the turn-on and shutdown of the make-up and exhaust hood fans. Clusters in the right-hand side of the complex power plane correspond to turn-on events, while clusters in the left-hand side correspond to shutdown events.

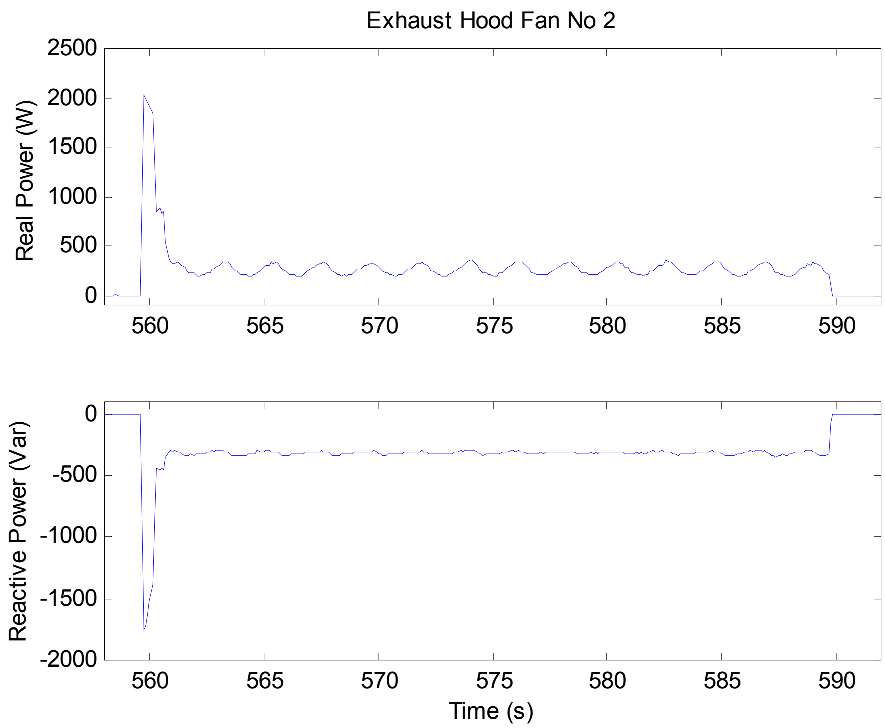
The exhaust fans and the make-up fan have the same scheduled turn-on and shutdown times, sometimes causing the fans to switch states (almost) simultaneously. In order to better simulate their actual operation, the exhaust and make-up fans were turned on and off individually and simultaneously during the load-database generation tests (Table 4).



a) Power Waveforms when both Hood Fans turn-on/shut-down together.



b) Fan No. 1 Power Waveforms



c) Fan No. 2 Power Waveforms

Figure 4-7 *Exhaust Hood Fans Power Waveforms.*

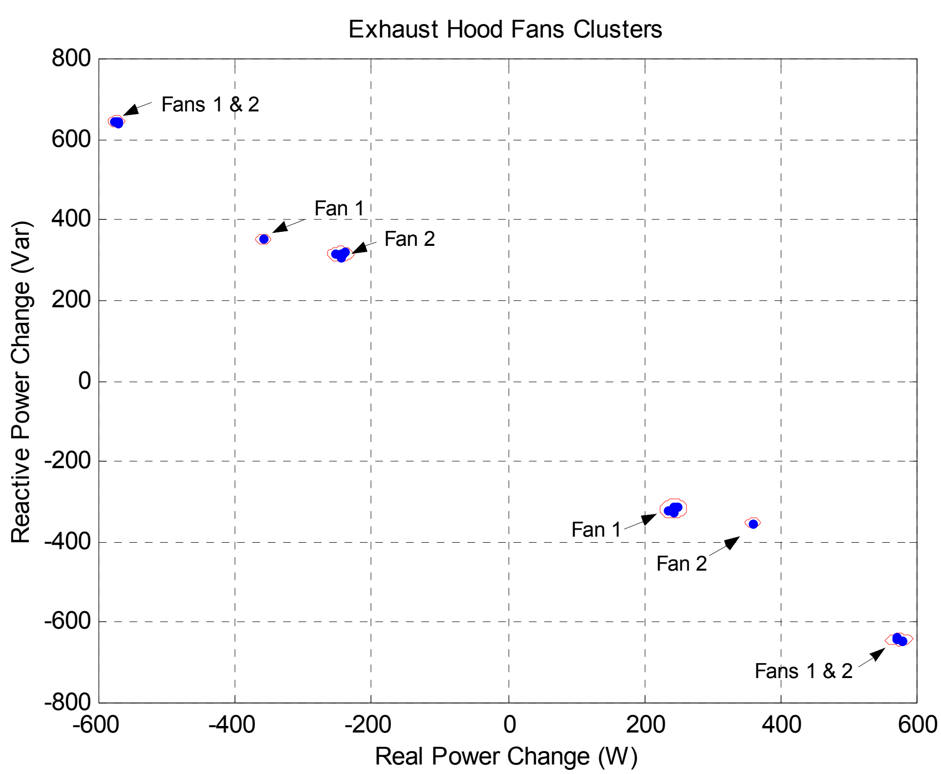


Figure 4-8 *Exhaust Hood Fans Clusters in Complex Power Space.*

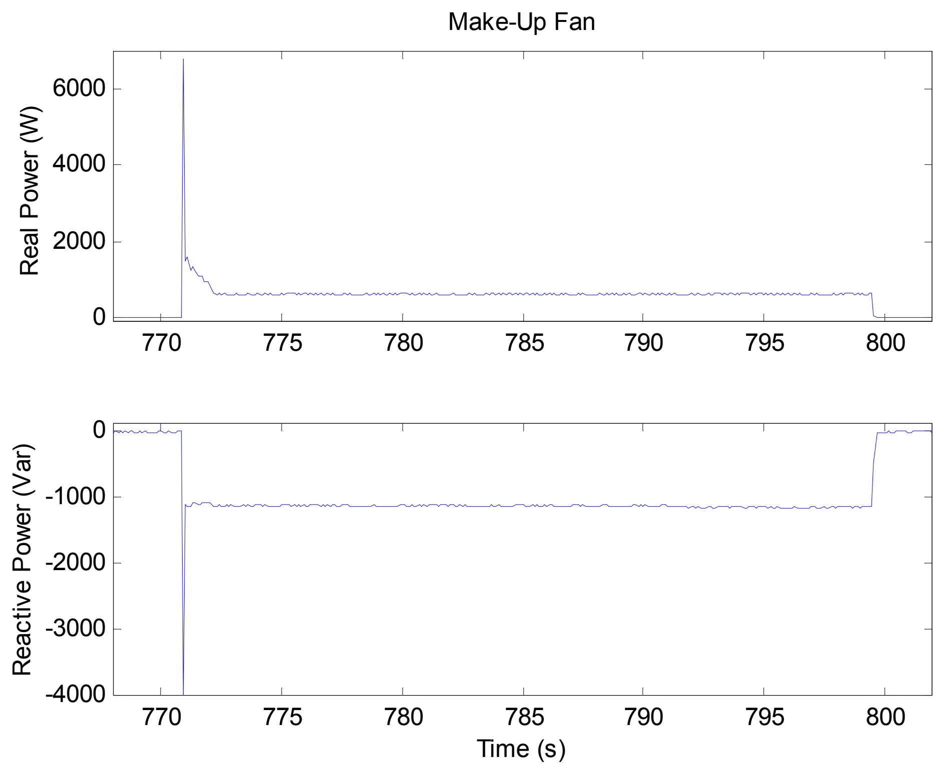


Figure 4-9 *Make-Up Fan Power Waveforms.*

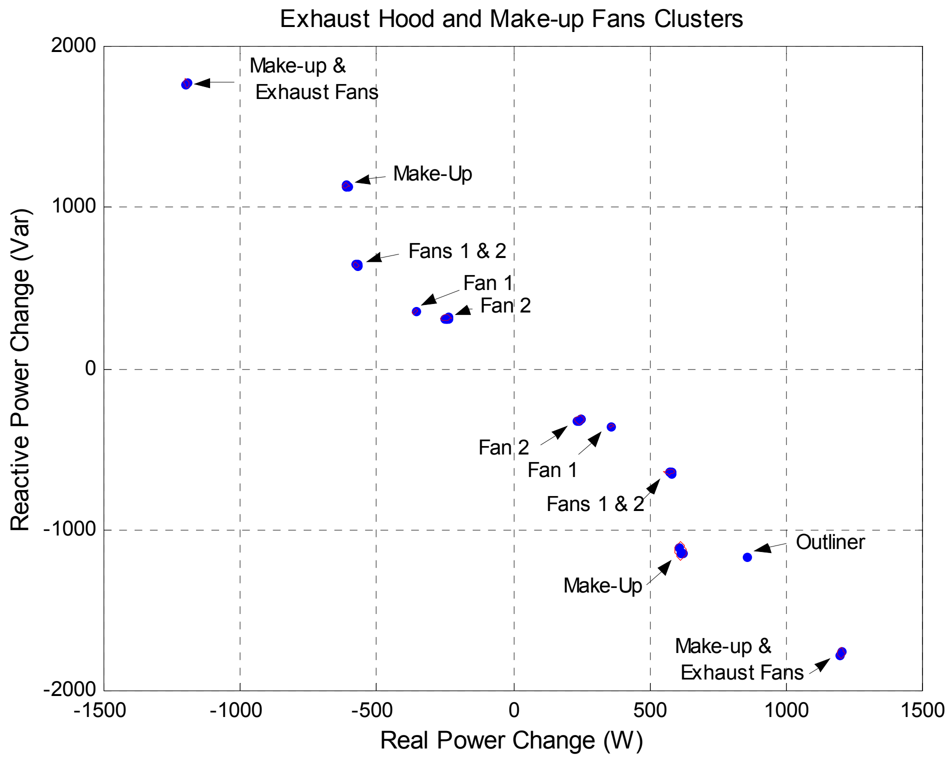


Figure 4-10 *Make-Up Fan and Exhaust Hood Fans Clusters in Complex Power Space.*

<u>HVAC Units (Heating Mode)</u>

Figure 4-11 shows the power waveforms characteristic of the lobby HVAC (LRTU) unit, and Figure 4-12 shows the kitchen HVAC (KRTU) power waveforms. Both units' waveforms were obtained during heating mode operation.

Electric consumption of the HVAC units during normal heating mode operation is due to the fans and control electronics of the units. Natural gas is used to provide heat in both HVAC units.

Two waveform plots are presented for the kitchen HVAC: the first plot (a) shows the power waveform during normal heating mode operation, while the second plot (b) shows a surge in the kitchen HVAC unit power consumption that lasts approximately 19 seconds, and is almost certainly due to abnormal operation of the unit compressor.

Figure 4-13 shows the HVAC units' steady-state power-change cluster plots in the complex power plane together with the make-up and exhaust hood fans. The points due to the kitchen HVAC power surge, and those corresponding to the simultaneous turn-on and shutdown of the make-up and exhaust hood fans, are not shown on the plot.

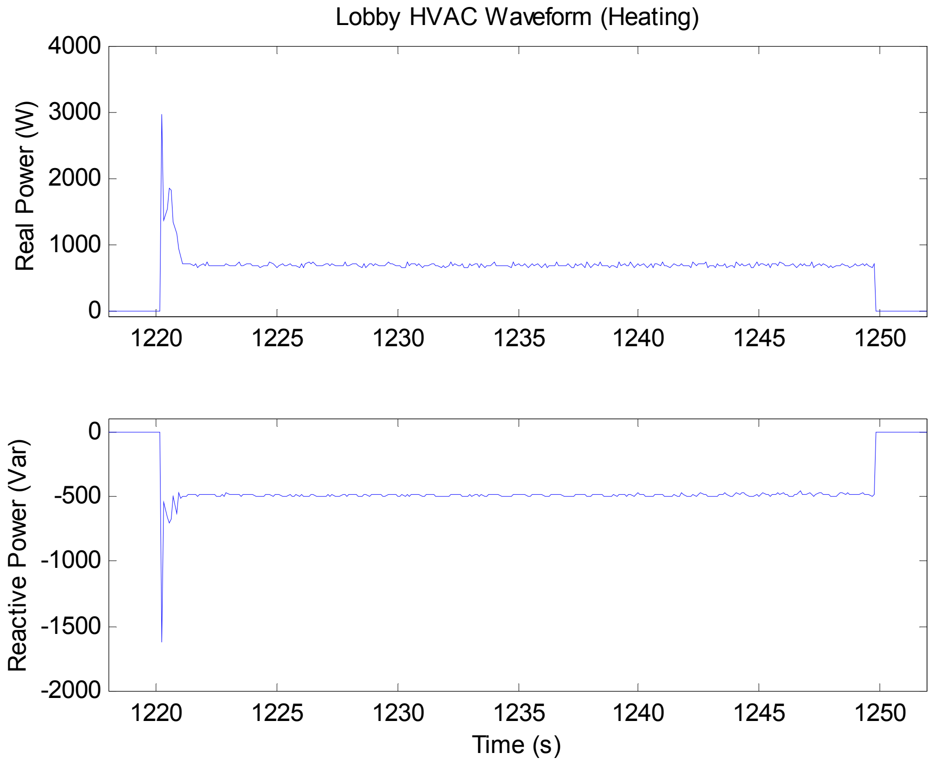
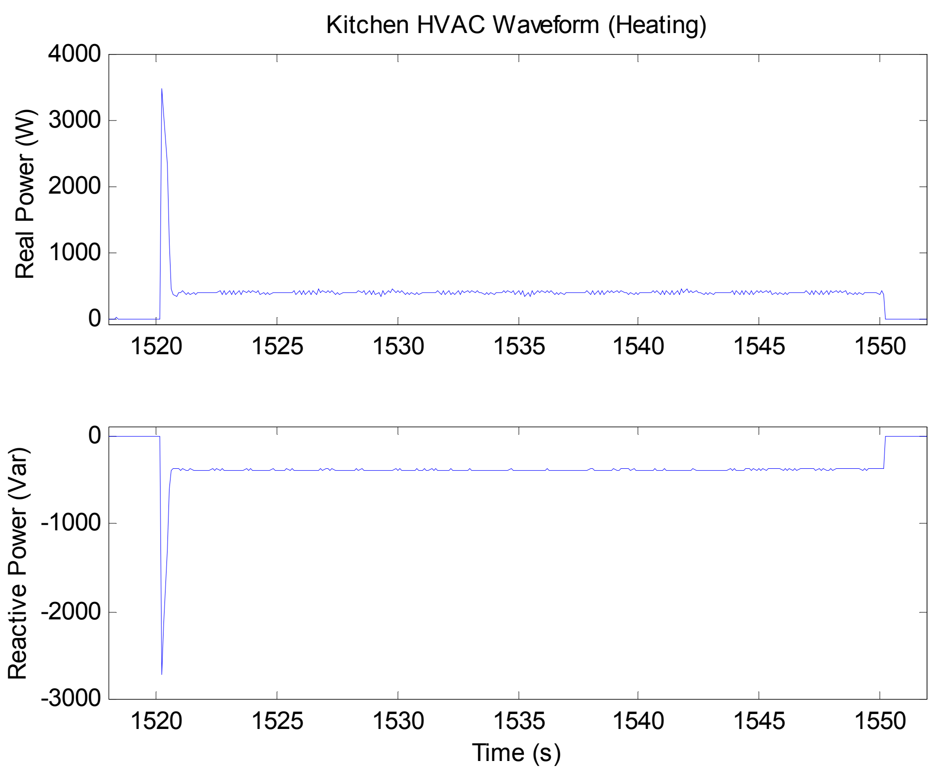
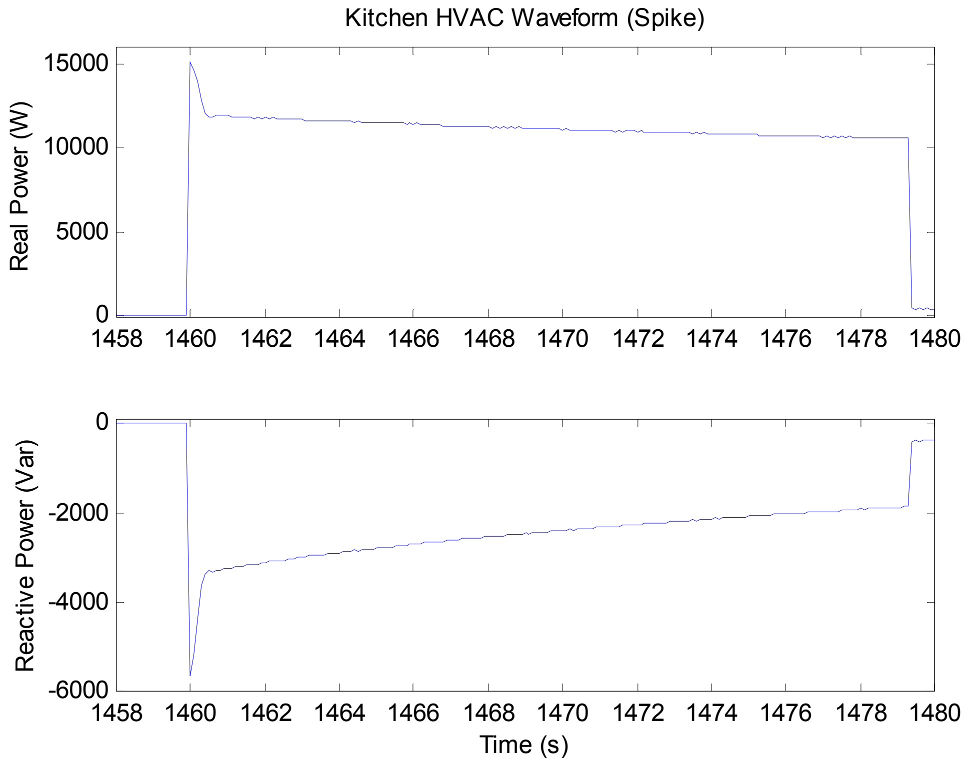


Figure 4-11 *Lobby HVAC Unit Power Waveforms.*



a) Normal Heating Operation



b) Power waveforms due to HVAC unit compressor

Figure 4-12 *Kitchen HVAC Unit Power Waveforms.*

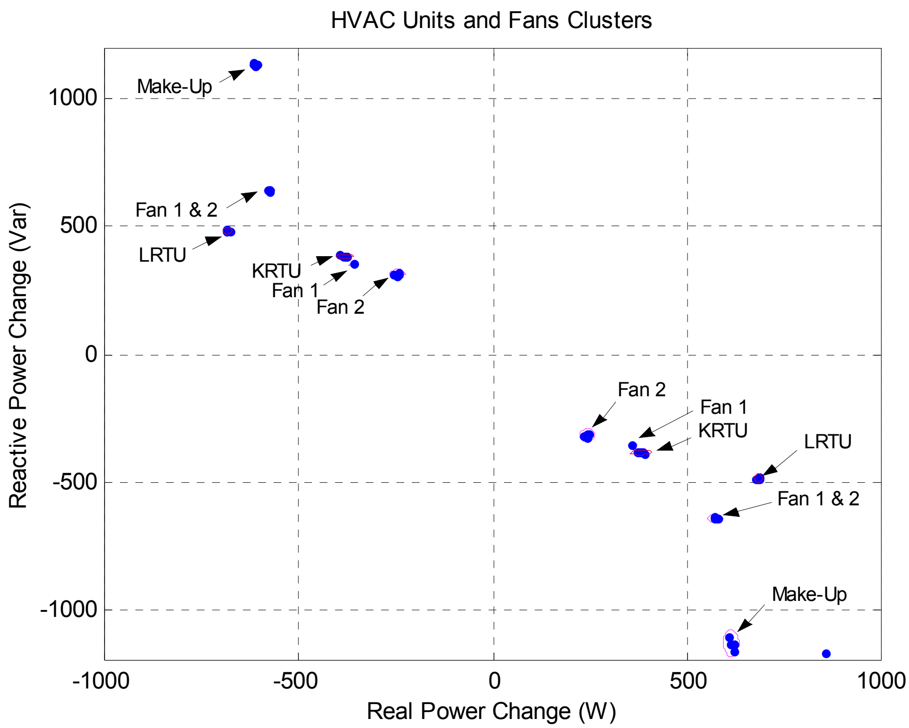
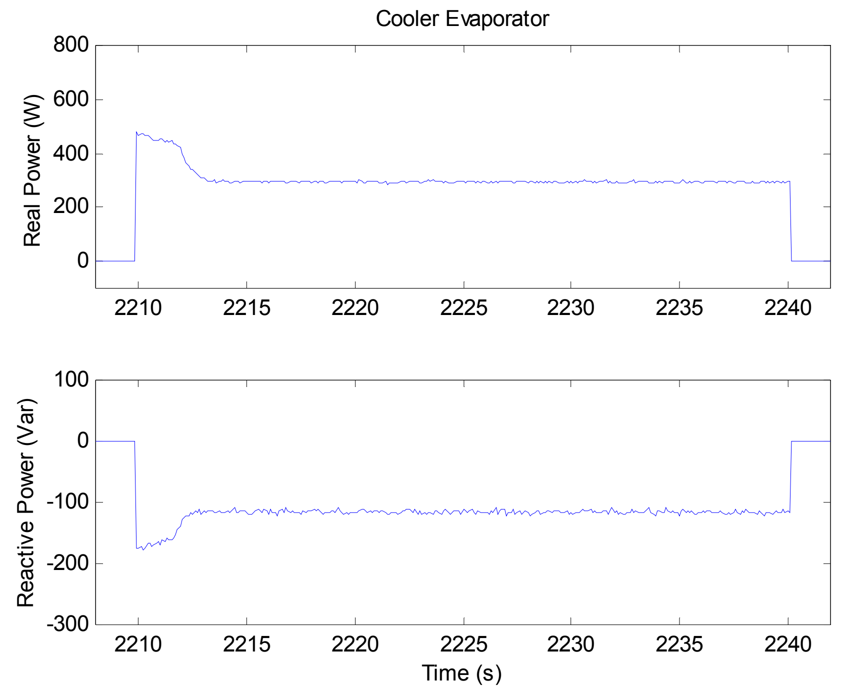


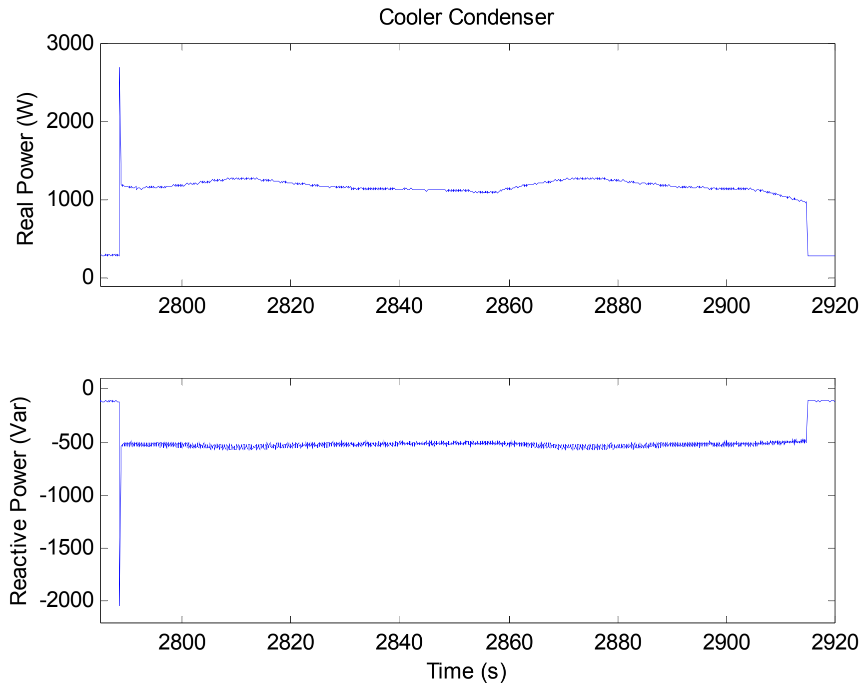
Figure 4-13 *HVAC Units and Fans Clusters in Complex Power Space.*

<u>Walk-in Cooler</u>

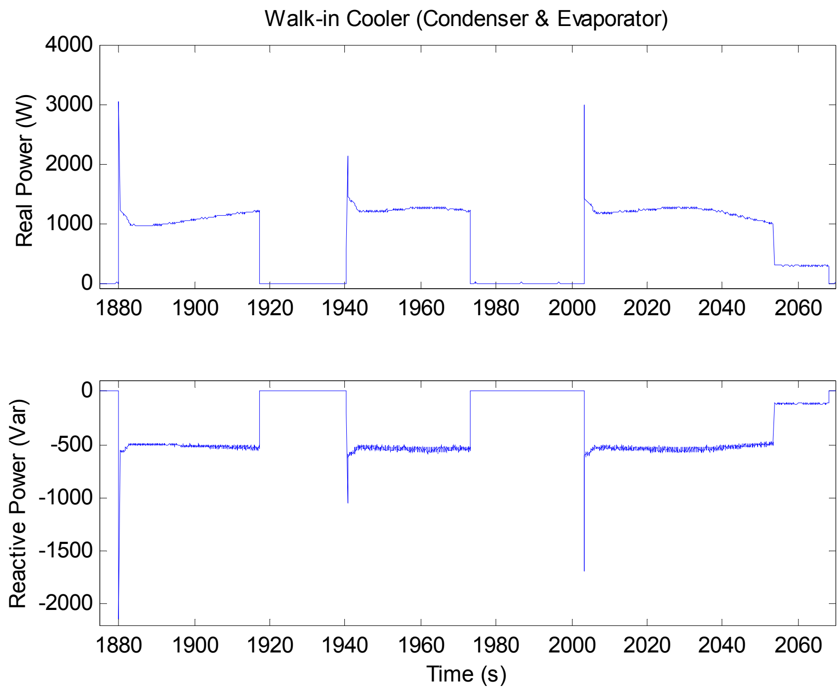
The walk-in cooler is composed of two separate units: The evaporator inside the refrigeration compartment, and the condenser outside. The evaporator contains the evaporator coil and fans, while the condenser contains the compressor, the condenser coil and fans.



a) Cooler Evaporator Unit



b) Cooler Condenser Unit



c) Cooler Condenser and Evaporator operating together

Figure 4-14 *Walk-in Cooler Power Waveforms.*

Three sets of tests were performed: the evaporator was turned on and off alone, the condenser was operated alone, and finally the condenser and evaporator were turned-on and off together. Figure 4-14 (a) to (c) show the power waveforms obtained during the three tests described.

<u>Walk-in Freezer</u>

Tests similar to the ones performed on the walk-in cooler were performed to the walk-in freezer. Figure 4-15 shows sample real and reactive power waveforms of the tests performed.

Although the freezer and cooler units are similar, the behavior shown by the walk-in freezer during the tests was different from the one shown by the cooler. The cooler condenser presented a sharp shutdown waveform, while the freezer condenser presented a shutdown waveform that was identified as two events, instead of a single event, by the GLR program. The GLR program also detected an additional turn-on event during the freezer operation.

These additional events on the freezer were treated as additional loads on the circuit, and resulted from the non-simultaneous turn-on and shutdown of the compressor and fans in the freezer-condenser. Figure 4-16 shows the refrigeration units' power change cluster plots. It is interesting to note that the cooler condenser shutdown cluster overlaps the second shutdown cluster of the freezer condenser.

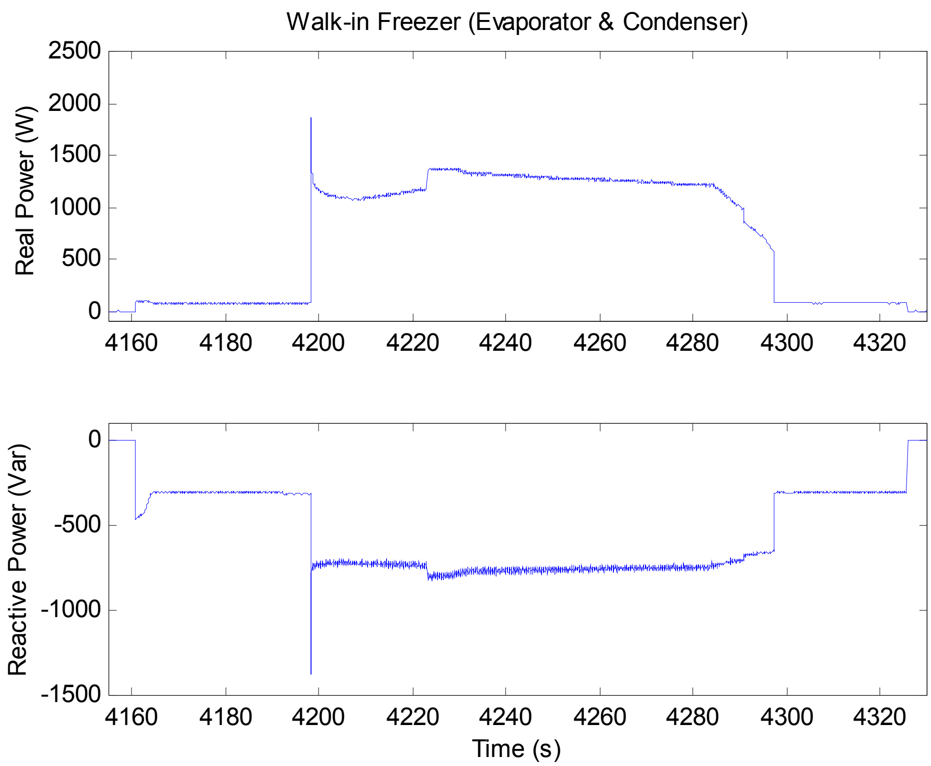
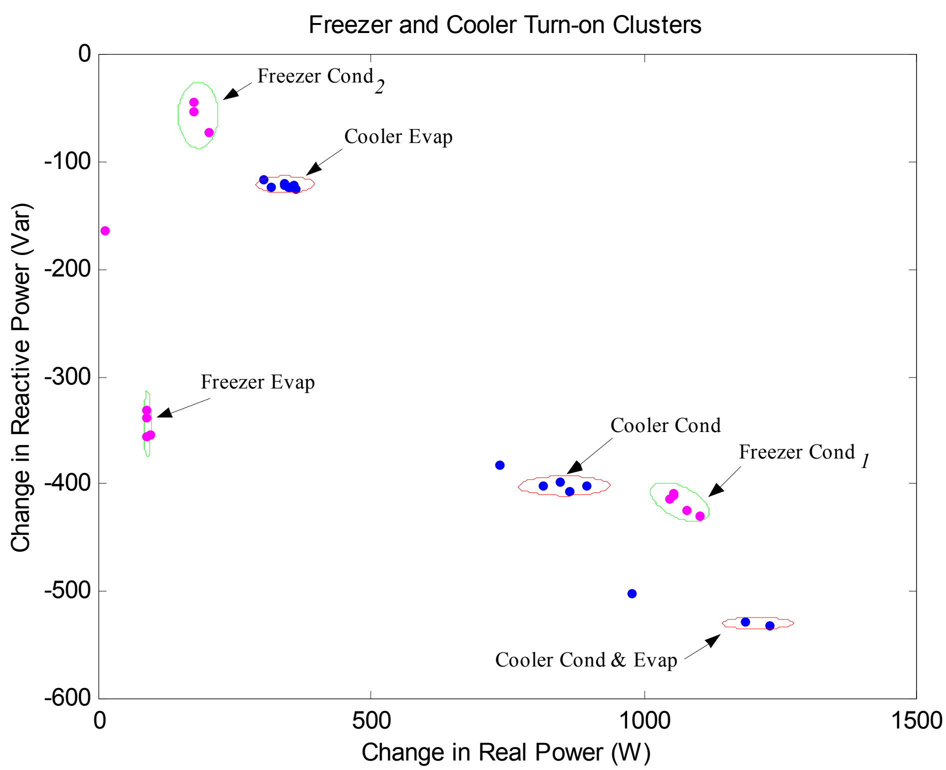
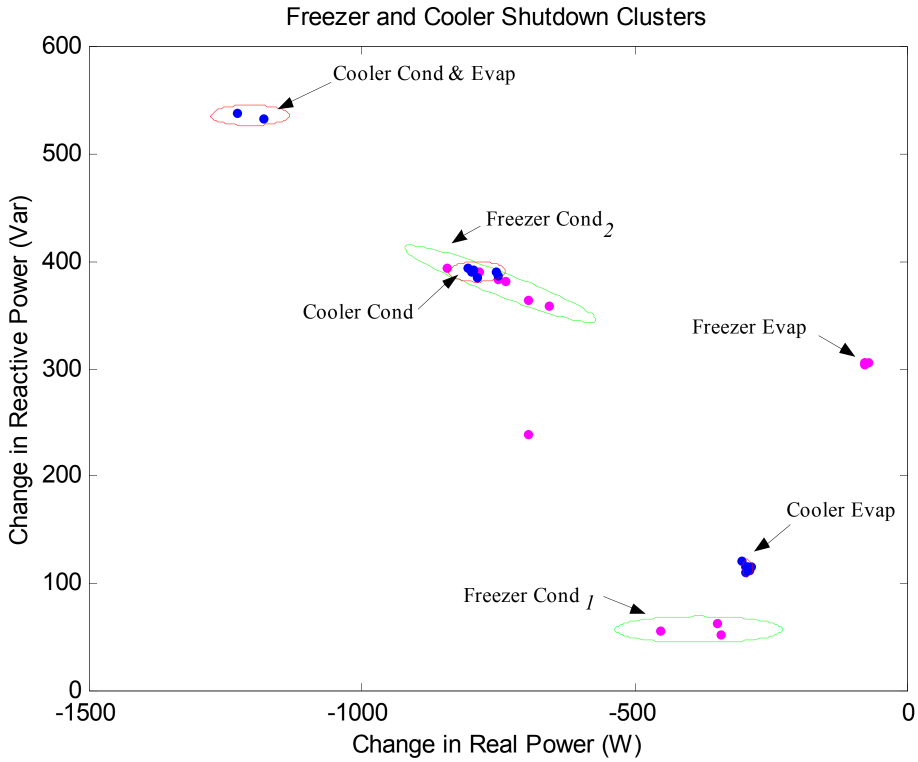


Figure 4-15 *Walk-in Freezer Power Waveforms.*



a) Turn-on Events Clusters



b) Shutdown Events Clusters

Figure 4-16 *Refrigeration Units Clusters in Complex Power Space.*

Initial Database Values

It can be seen from the cluster plots that the loads surveyed in the restaurant have turn-on and shutdown events in the fourth and second quadrants, respectively, of the complex power change space.

Table 5 contains the statistical data extracted from the power-change clusters obtained from the test data series. As mentioned previously, these results were obtained manually and with a relatively small sample. As the number of samples taken during the operation of the NILM increases, the database could (and would) be updated to reflect the new information.

After the initial database was created, the load database was updated to include the loads that were not addressed during the manual test sequence (for example the convection oven) and that are being monitored by the NILM system (Table 1). The update was done using the load-event information obtained from the parallel metering (sub-metering), as well as data obtained from the NILM system during its normal operation.

Table 5 *Initial Database Values.*

Load	Event	Mean Power Change		Standard Dev.	
		Real	Reactive	Real	Reactive
Hood Fan No. 1±	On Off	358.91 -359.27	-352.91 351.94	*3.0* *3.0*	*2.0* *2.0*
Hood Fan No. 2	On Off	242.82 -245.86	-317.38 315.48	5.1 4.974	6.04 4.49
Hood Fans 1 & 2	On Off	573.89 -562.42	-642.58 639.6	4.98 8.22	3.62 4.43
Make-up Fan	On Off	606.13 -609.21	-1131.5 1132.4	14.26 3.04	22.94 3.48
Make-up & Hoods	On Off	1200.3 -1197.7	-1764.0 1770.0	3.33 2.08	8.33 6.56
Lobby HVAC (Heat)	On Off	683.572 684.138	485.848 484.968	3.294 3.207	3.804 3.521
Kitchen HVAC (Heat)	On Off	380.325 -382.121	384.818 383.997	6.774 5.757	2.452 2.147
Cooler Evaporator	On Off	341.879 -293.513	-121.126 114.388	17.962 3.244	2.619 1.755
Cooler Condenser	On Off	854.308 789.485	401.887 390.321	27.949 17.398	3.031 3.154
Cooler Cond. + Evap.	On Off	1207.8 1205.2	529.6 535.9	22.05 23.99	1.845 3.147
Freezer Evaporator	On Off	77.21 -76.72	-308.48 304.55	2.22 1.82	1.22 2.49
Freezer Condenser	On 1 On 2 Off 1 Off 2	1066.0 182.49 -382.659 -746.549	-416.8 -56.705 57.245 378.99	20.196 12.275 51.518 59.873	8.104 11.227 4.102 3.90

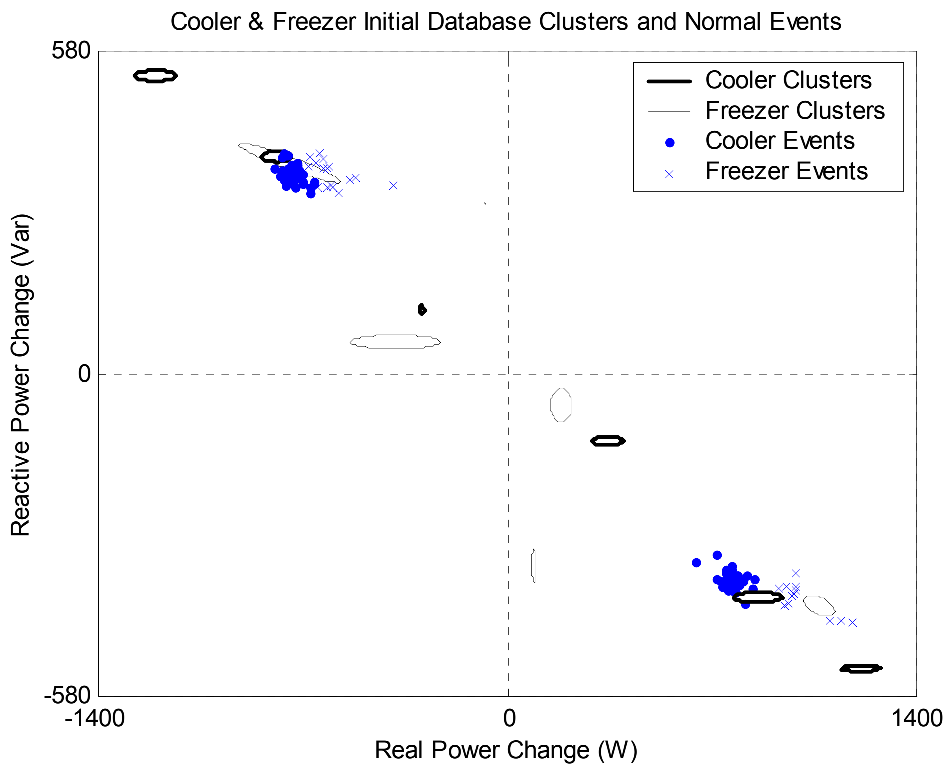
± *Only one sample of Hood Fan No. 1 was taken. The standard deviation was chosen to define an area similar to Fan's No. 2*

4.2.3 Database Update and Maintenance

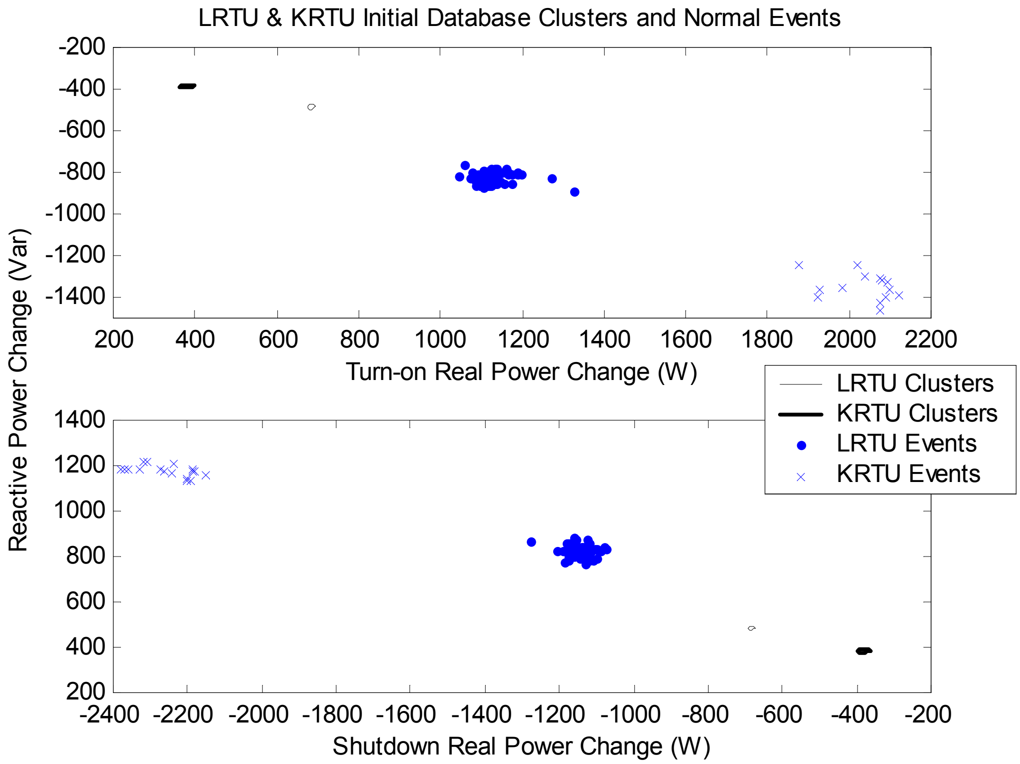
Figure 4-17 shows an example of the turn-on and shutdown clusters formed during the normal operation of the loads in the restaurant and the initial database load event areas. (Figure 4-17 does not present the oven clusters since its database values were not obtained during the initial training period.) It can be seen from the figure that most of the clusters observed during the training period differ from the clusters observed during the normal operation of loads.

The discrepancy between the database values and the actual operation clusters is mainly due to baseline power consumption of the loads that was assimilated into the power change values obtained when the loads were turn-on and off manually, resulting in event power change values that were higher than the actual values. Classification using the initial database values was unsuccessful.

It was necessary to update the load database used to classify the events using data collected from the site during its normal operation. These data were compared to the sub-metering data collected using the C180 system in order to associate the clusters formed with the actual loads. Appendix B presents the process followed to obtain the new database from the recorded events and the C180 sub-metering data.



a) Cooler and Freezer Clusters



b) HVAC Units Clusters.

Figure 4-17 *Power Change Clusters obtained during Normal Operation and Initial Database*

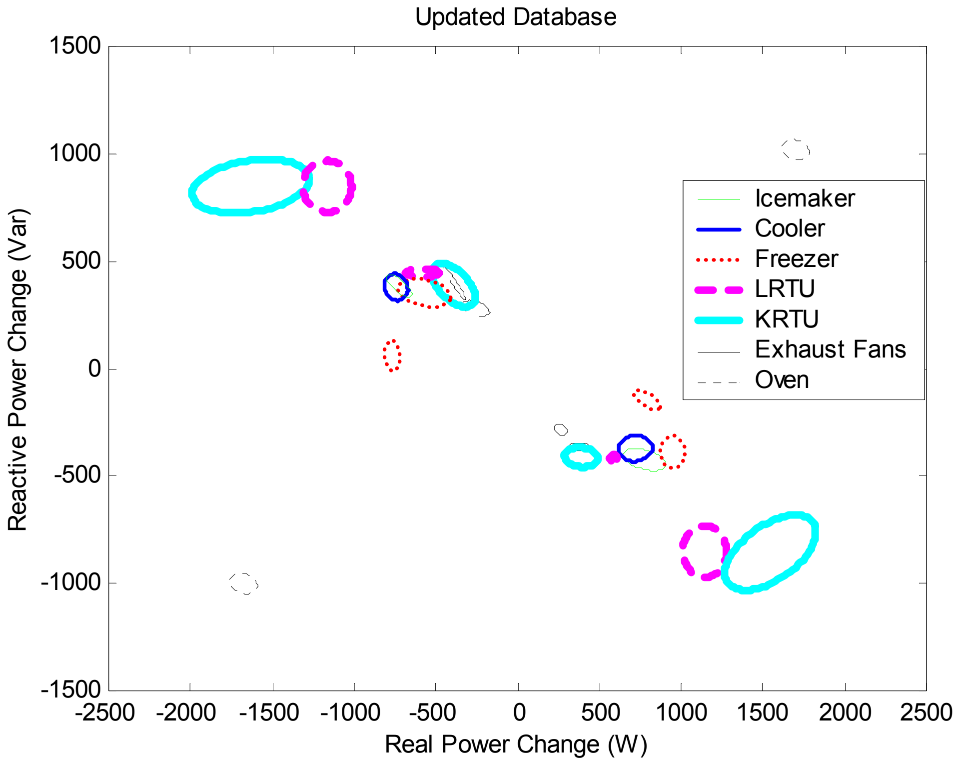
Table 6 presents the updated database values obtained using data from multiple days of normal operation. Figure 4-18 shows the plots in the complex power space corresponding to the database values presented in Table 6.

The following observations on the load database clusters are obtained from Figure 4-18, and Table 6:

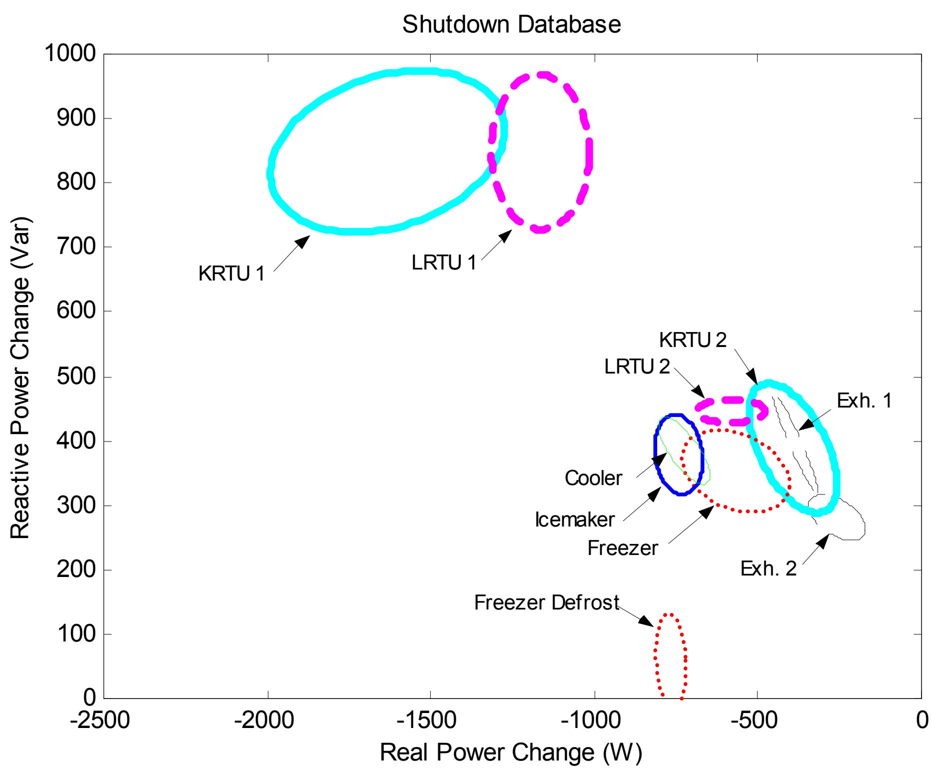
- All the clusters are located on the second and fourth quadrants of the complex power space, with the exception of the convection oven, whose clusters are located on the first and third quadrants.
- The walk-in cooler and icemaker event clusters overlap significantly, both during shutdown and turn-on. Freezer cluster overlap with the cooler and icemaker is relatively small.
- The fans and the rooftop air-conditioning unit also present some overlapping. The shutdown event cluster of one exhaust fan unit is totally enclosed by one of the shutdown event clusters of the kitchen roof top unit.
- Overlap is small between event clusters of the kitchen and the lobby roof top units.

***Table 6** Current Database Values.*

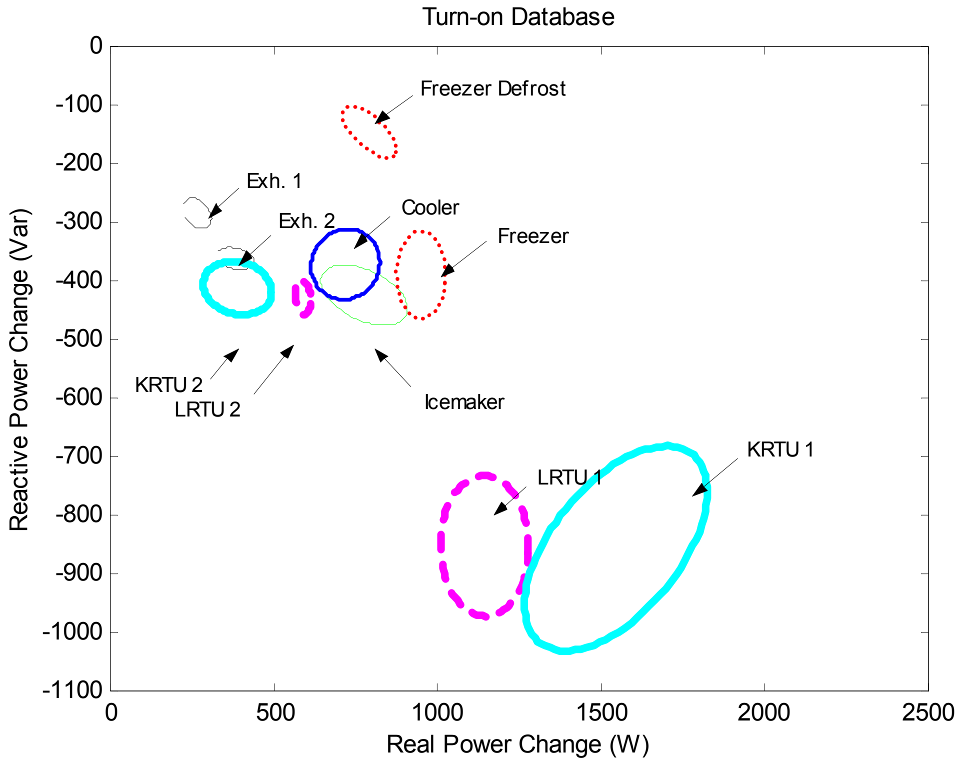
Event Name	Mean Power Change		Standard Deviation		Cluster	Average
	Real	Reactive	Real	Reactive	Angle	Power
Ice_On	775.86	-424.36	45	15	0.197	675
Ice_Off	-725.86	384.61	30	10	0.526	0
Cooler_On	718.2	-371.98	35	20	-0.05	1140
Cooler_Off	-742.81	378.59	25	20	0.351	284
Freezer1_On	949.54	-389.54	25	25	0.203	949.54
Freezer1_Off	-568.26	352.51	55	20	0.138	0
Freezer2_On	791.19	-146.26	30	10	0.399	791.19
Freezer2_Off	-766.32	58.182	15	25	-0.147	0
LRTU1_On	1143	-852.52	45	40	0.078	1143
LRTU1_Off	-1165.5	847.87	50	40	0.039	0
LRTU2_On	588.64	-427.73	7.5	10	-0.292	588.64
LRTU2_Off	-583.33	445.92	35	6	0.00	0
KRTU1_On	1544.8	-856.75	100	45	-0.426	1544.8
KRTU1_Off	-1631.9	848.89	120	40	-0.107	0
KRTU2_On	388.22	-412.45	35	15	0.074	388.22
KRTU2_Off	-393.11	388.45	50	25	0.537	0
KRTUs_On	11262	-2544.5	150	65	0.249	11262
KRTUs_Off	-10439	1679.8	160	35	0.305	0
Exh1_On	380.73	-362.07	20	6	0.092	380.73
Exh1_Off	-386.41	397.15	35	5	0.849	0
Exh2_On	265.38	-284.79	15	8	0.278	265.38
Exh2_Off	-258.19	281.11	30	10	0.233	0
Oven_On	1697	1019.1	29	15	0.142	1697
Oven_Off	-1676.3	-1000.3	29	15	0.201	0



a) Total Database Clusters



b) Shutdown Cluster Detail



c) Turn-On Clusters Detail

Figure 4-18 *Updated Database Cluster Plots.*

4.2.4 Event Classification Results

The event classification module correctly classified **91.4%** of detected events. Figure 4-19 shows the distribution of events by load observed on the monitored circuit. It can be seen that the majority of the events correspond to the oven turn-on and shutdown events. The events generated by the oven are sufficiently distinct from the events generated by the other loads on the circuit.

The oven is the only load on the circuit that has its event clusters on the first and third quadrant of the complex power space, while all other loads have their event clusters in the second and fourth quadrants. When the oven events were removed from the classification set, the accuracy of the classification module dropped to **88.4%** correct classification.

The classification results presented previously take into account all correctly identified events, regardless of conflicts with the load states. A conflict is generated when a load event does not cause a change in the load state. For example, a shutdown event when the load is registered as being off. When events that generate conflicts were not considered as correctly classified events, the accuracy of the module dropped to **85.4%**.

Event Class	Occurrences
No Identified	1.4 %
Icemaker	1.1%
Cooler	8.7 %
Freezer	6.7^%
LRTU	13.4 %
KRTU	7.7 %
Exhaust Fans	0.6 %
Oven	60.5 %

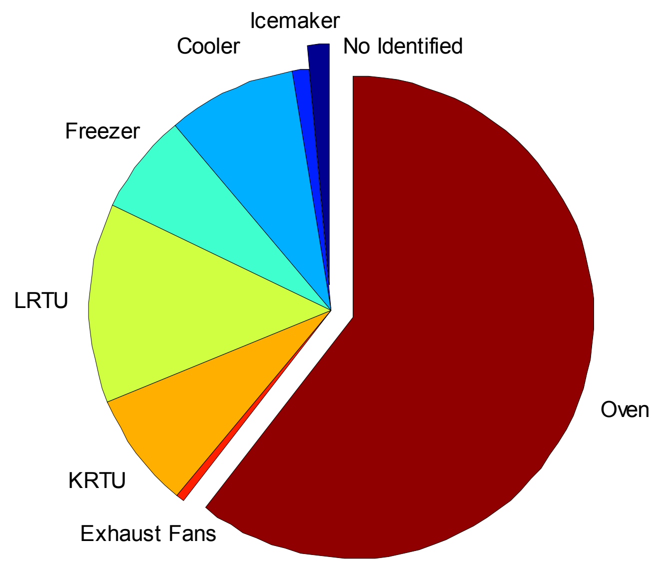


Figure 4-19 *Load Events Distribution on Monitored Circuit.*

Figure 4-20 and Table 7 summarize the results obtained from the NILM classification module, both when all correctly classified events are considered, and when conflicting events are removed from the correctly classified events set.

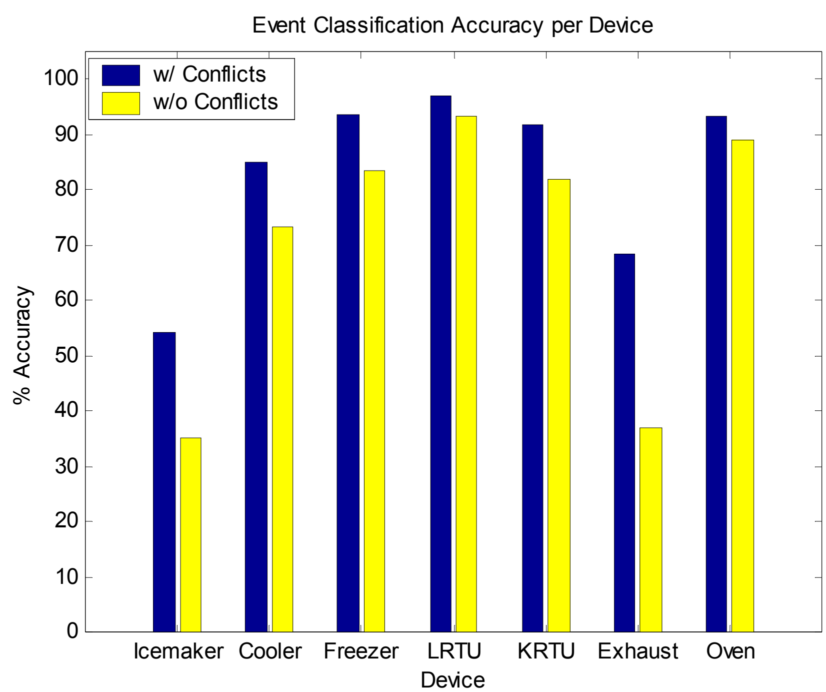


Figure 4-20 *Accuracy of Event Classification Module.*

***Table** 7 Classification Module Results.*

	Classification Accuracy	Load Classification Accuracy						
		Icemaker	Cooler	Freezer	LRTU	KRTU	Exhaust	Oven
All Events	**91.4%**	54.05 %	85.02 %	93.59 %	97.01 %	91.88 %	68.42 %	93.42 %
No Conflicts	**85.4%**	35.14 %	73.29 %	83.33 %	93.18 %	81.92 %	36.84 %	88.95 %

Most of the errors during the classification process can be attributed to the following causes:

1) Events occurring simultaneously. An algorithm to deal with the power change detected when two or more events occur simultaneously has not been implemented yet, therefore events comprising multiple loads events are classified as "non identified". One of the problems with composite events is that the registered power change values do not correspond to the addition of the individual events.
2) Overlapping Load Clusters. The method used for classification is based on measuring the distance from an event point in the complex power space to the different cluster centers and choosing the cluster at the minimum distance from the point. Overlapping clusters increase classification errors because they increase the number of clusters that are at a minimum distance from a given event point. An additional dimension or parameter, such as transient behavior, harmonic content or actual building operation information, is needed in order to differentiate among members of distinct clusters.
3) Steady-State Power Change Variations. The measure of the steady-state power changes of an event is affected by such factors as system noise and load conditions of the machine, for example temperature or pressure differentials. These variations in the measured steady state power change for a given event also contribute to the classification errors.

4.3 Performance of Energy Estimation Module

The performance of the Energy Estimation Module depends, mainly, on two factors: the results obtained from the event detection and event classification modules and their accuracy, and the average power consumption values contained in the load database. The number of events for each load during the reported period also has an effect on its energy-use estimation.

The energy consumption values obtained from the NILM program were compared to the energy consumption values reported by the parallel metering system for seven days of measurements. The results are summarized in Table 8.

Total energy consumption reported by the NILM system was in close agreement with the total energy consumption reported by the C180 system (<3% error) while the energy consumption estimation for the individual appliances was not. This is due to the fact that the total energy consumption is computed using the power data obtained from the power measurement module, while the energy consumption for the individual loads is based on the load-event information obtained from the event-classification module.

It is interesting to note that as the number of events for some of the devices increases, their energy estimation tends to improve. For example, Table 8 shows that the energy estimation for the lobby roof top unit (LRTU) was within 12% of the C180 energy values on the days that the LRTU had a lot of activity, and had an error of 228% when the LRTU only had a single turn-on and a single shutdown during the day.

***Table 8** Energy Estimation Module Performance.*

Device		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Overall
Icemaker	**# Events**	10	8	6	7	6	17	18	72
	C180	8.006	6.429	5.945	4.658	10.193	8.85	6.993	51.07
	NILM	6.407	2.802	10.816	2.529	6.247	10.193	11.41	50.40
	% Error	-19.97%	-56.42%	81.93%	-45.71%	-38.71%	15.18%	63.16%	-1.31%
Cooler	**# Events**	67	62	74	43	61	96	111	514
	C180	16.227	14.352	12.078	7.781	12.271	18.66	22.823	104.19
	NILM	14.998	17.869	12.499	8.443	13.014	20.945	25.573	113.34
	% Error	-7.57%	24.51%	3.49%	8.51%	6.05%	12.25%	12.05%	8.78%
Freezer	**# Events**	53	42	58	35	46	46	56	336
	C180	13.372	15.736	14.101	9.254	14.072	23.00	23.741	113.28
	NILM	20.804	24.187	14.579	12.108	20.452	31.104	30.298	153.53
	% Error	55.58%	53.70%	3.39%	30.84%	45.34%	35.23%	27.62%	35.53%
LRTU	**# Events**	2	29	176	95	167	131	209	809
	C180	9.198	7.214	12.099	5.822	10.347	6.57	11.708	62.96
	NILM	30.047	7.426	11.419	5.292	9.273	7.334	13.132	83.92
	% Error	226.67%	2.94%	-5.62%	-9.10%	-10.38%	11.63%	12.16%	33.29%
KRTU	**# Events**	(127)	(122)	6	2	14	40	13	75
	C180	15.768	11.325	25.253	10.896	24.364	35.24	31.987	154.83
	NILM	33.067	18.297	28.283	21.904	36.579	45.79	39.524	223.44
	% Error	109.71%	61.56%	12.00%	101.03%	50.14%	29.94%	23.56%	44.31%
Exhaust Fans	**# Events**	4	4	4	4	4	4	6	30
	C180	7.941	7.879	8.307	2.472	7.759	11.47	10.371	56.20
	NILM	10.570	12.856	9.881	6.161	15.293	19.151	22.781	96.69
	% Error	33.11%	63.17%	18.95%	149.23%	97.10%	66.97%	119.66%	72.05%
Oven	**# Events**	507	451	529	121	518	590	505	3221
	C180	6.984	6.672	7.398	1.986	6.628	8.52	7.128	45.32
	NILM	7.427	6.873	6.527	1.896	6.490	9.3769	7.162	45.75
	% Error	6.34%	3.01%	-11.77%	-4.53%	-2.08%	10.06%	0.48%	0.95%
Total	**C180**	91.402	83.356	98.668	50.742	98.914	128.69	134.45	686.22
	NILM	91.616	83.041	95.773	51.208	98.350	129.42	133.92	683.33
	% Error	0.23%	-0.38%	-2.93%	0.92%	-0.57%	0.57%	-0.39%	-0.42%

4.3.1 Factors affecting Energy Estimation Results

A given load power waveform is approximated using square waveforms to estimate its energy consumption. The square waveforms are defined using the time of the load events, obtained from the load classification module, and the average power consumption values contained in the load database. Figure 4-21 depicts the approximation performed graphically for an arbitrary load.

The energy estimation results depend mainly on two factors: the *Average Power Values* contained in the load database, and the correct identification of the load events.

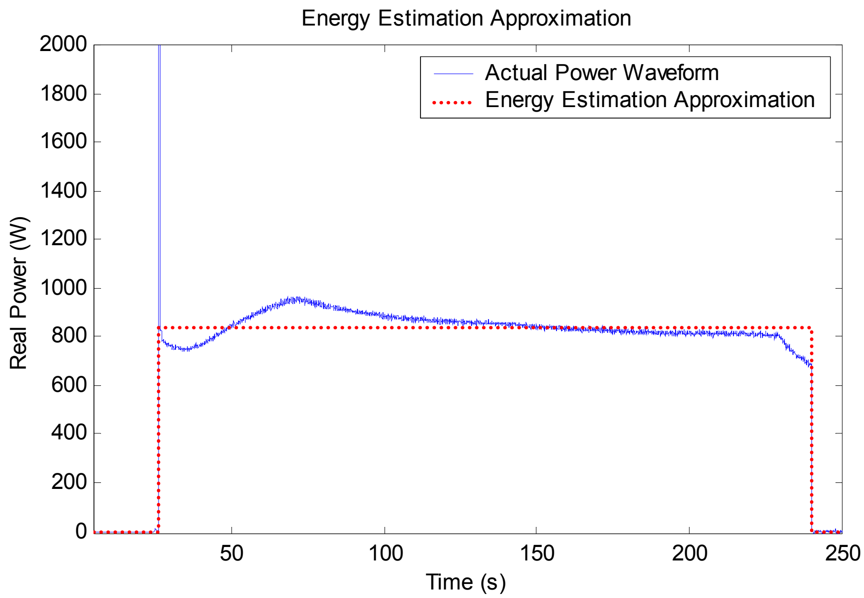


Figure 4-21 *Power Waveform Approximation for Energy Estimation.*

<u>Average Power Values</u>

The average power consumption values are obtained experimentally from the NILM system training data, and the training data obtained simultaneously by the parallel metering system.

The initial database (Table 5) assumes zero stand-by or residual power consumption from the loads, that is, it considers only load power consumption during the periods between turn-on and shutdown events, and ignores any consumption by the loads that might exist after a detected shutdown event. However, some of the appliances in the building, specifically the walk-in cooler and freezer and the lobby roof top unit, present a stand-by power consumption or "off state" consumption (Figure 4-22).

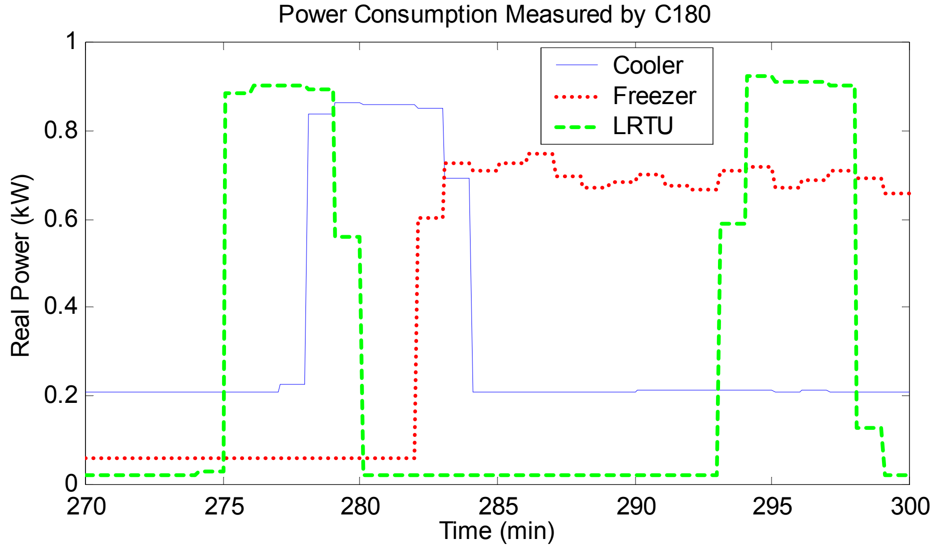


Figure 4-22 *"Off State" Power Consumption as measured by C180 System.*

The average power values in the load database were therefore modified to take into account the "off state" consumption of the loads. The device power and energy consumption values obtained from the C180 system, together with the NILM energy estimates are used to compute the new average power values used in the database (Table 6). Table 9 presents, as an example, the changes made to the cooler database values.

Table 9 *Average Power Values Changes in Load Database.*

Event Name	Initial Avg. Power	Updated Avg. Power
Cooler_On	718.2	1140
Cooler_Off	0	284

The energy estimates presented in Table 8 were computed using the average power values that take into account the "off state" consumption of the loads.

Event Detection and Classification

Figure 4-23 shows a simple example (only two events and a single load) to illustrate the dependence of the energy estimation on the correct identification of turn-on and shutdown events. The example makes the following assumptions: the initial state of the load is known ("off state"), the load has an idealized operation, and the average power consumptions are also known. The time units are irrelevant and the period considered is the length shown in the figure.

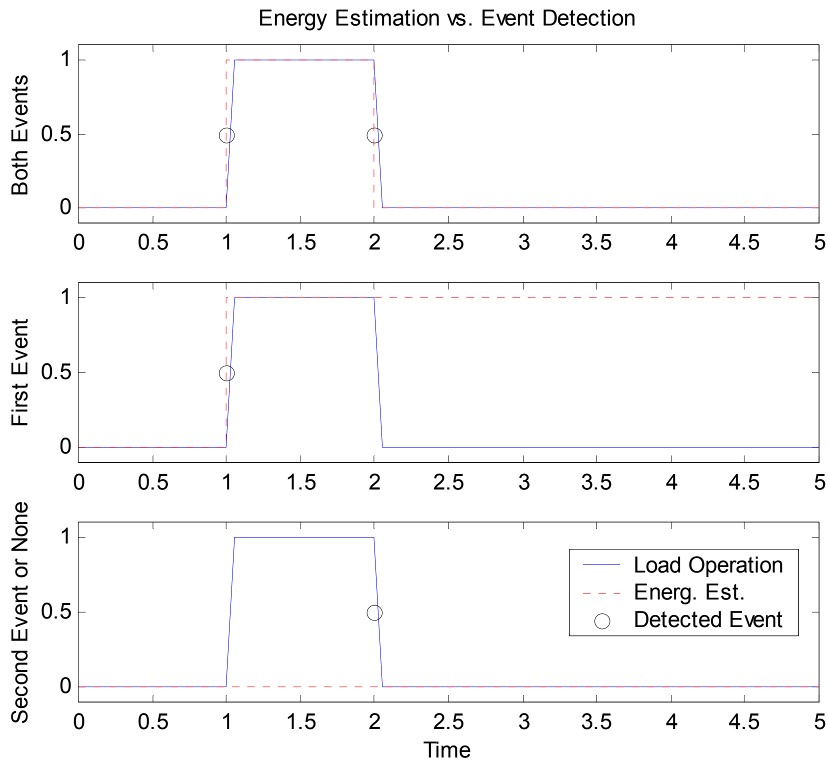


Figure 4-23 *Effect of Event Detection/Classification on Energy Estimation.*

The first panel shows the case when both events are correctly identified. In this case the energy consumption estimation using equation gives the actual energy consumption of the load. The second panel shows that case when the shutdown event is missed, either by non-detection, or misclassification. The energy consumption estimation would be four times larger than the actual load consumption since the load shutdown was not registered.

The third panel shows two cases that give the same results: both events are missed or the turn-on event is missed. The case where the two events are missed is trivial since no activity for the load would be registered and hence no energy consumption would be reported. When the turn-on event is missed, the energy estimation module discards the detected shutdown event because it would generate a conflict with the previous load state registered (The load is already off). Missing the turn-on event therefore results in zero energy-consumption estimation, as in the case of both events missed.

4.3.2 Energy Estimation Improvements

Energy estimation is highly dependent on the correct identification and classification of the load events. Missing load events have a considerable impact on the energy estimation, especially when the loads have low activity rates during the monitored period. Missed load events are caused by the non-detection of the events or their misclassification.

In order to improve energy estimation results, different methods were investigated in order to obtain better event detection and load classification.

Improving Event Detection

A multi-sampling rate GLR program was used to improve event detection. The use of the multi-sampling rate GLR was expected to yield better energy estimation results by reducing the number of missed events.

The detection of events by the GLR algorithm depends on the sampling rate of the analyzed data. A low sampling frequency (high sampling period) is prone to miss shortly spaced events, while a high sampling frequency might find these events, but at the expense of a higher computational cost and possibly more false alarms.

Events were detected and the energy consumption estimated when the multi-sampling rate GLR algorithm used sampling periods of one second (1s GLR) and half a second (0.5s GLR)[4]. Event detection improved when using the multi-sampling rate GLR instead of the single rate GLR program.

Energy estimation, however, did not consistently improve with the better detection results. Table 10 shows and compares the energy estimation results when using the single-sampling rate GLR (1s GLR) and the multi-sampling rate GLR (0.5s and 1s GLR) on seven days of data. The results in the table are shown as percentage errors of the NILM energy estimation relative to the energy values obtained from the C180 system. A negative error change (**bold** typeface) indicates an improvement on the energy estimation (for the particular device and day) achieved by using the multi-sampling rate GLR instead of the single-rate GLR.

Table 10 *Energy Estimation Errors using Multi-Sampling Rate Event Detection.*

Device			Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Week
Icemaker	**C180**	**kWh**	8.006	6.429	5.945	4.658	10.193	8.85	6.993	51.07
	1s GLR	**kWh**	6.407	2.802	10.816	2.529	6.247	10.193	11.41	50.40
		% Error	-19.97%	-56.42%	81.93%	-45.71%	-38.71%	15.18%	63.16%	-1.31%
	MSR GLR	**kWh**	6.407	6.404	10.816	2.529	6.247	10.193	11.410	54.01
		% Error	-19.97%	-0.39%	81.93%	-45.71%	-38.71%	15.18%	63.16%	5.76%
		Change	0.00%	**-56.03%**	0.00%	0.00%	0.00%	0.00%	0.00%	4.45%
Cooler	**C180**	**kWh**	16.227	14.352	12.078	7.781	12.271	18.66	22.823	104.19
	1s GLR	**kWh**	14.998	17.869	12.499	8.443	13.014	20.945	25.573	113.34
		% Error	-7.57%	24.51%	3.49%	8.51%	6.05%	12.25%	12.05%	8.78%
	MSR GLR	**kWh**	14.998	17.937	12.204	8.443	13.094	21.172	25.292	113.14
		% Error	-7.57%	24.98%	1.04%	8.51%	6.71%	13.46%	10.82%	8.59%
		Change	0.00%	0.47%	**-2.45%**	0.00%	0.66%	1.21%	**-1.23%**	**-0.19%**
Freezer	**C180**	**kWh**	13.372	15.736	14.101	9.254	14.072	23.00	23.741	113.28
	1s GLR	**kWh**	20.804	24.187	14.579	12.108	20.452	31.104	30.298	153.53
		% Error	55.58%	53.70%	3.39%	30.84%	45.34%	35.23%	27.62%	35.53%

[4] The notation *1s GLR* refers to the GLR algorithm using a 1 second sampling period. Similarly *0.5s GLR* is used when the GLR uses sampling period of half a second.

Table 10 *Energy Estimation Errors using Multi-Sampling Rate Event Detection.*

Device			Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Week
	MSR	kWh	15.524	20.775	14.046	7.552	17.717	19.466	25.293	120.37
	GLR	% Error	16.09%	32.02%	-0.39%	-18.39%	25.90%	-15.37%	6.54%	6.26%
		Change	**-39.49%**	**-21.68%**	**-3.00%**	**-12.45%**	**-19.44%**	**-19.86%**	**-21.08%**	**-29.27%**
LRTU	C180	kWh	9.198	7.214	12.099	5.822	10.347	6.57	11.708	62.96
	1s	kWh	30.047	7.426	11.419	5.292	9.273	7.334	13.132	83.92
	GLR	% Error	226.67%	2.94%	-5.62%	-9.10%	-10.38%	11.63%	12.16%	33.29%
	MSR	kWh	30.047	6.974	11.134	5.098	8.474	6.879	13.132	81.74
	GLR	% Error	226.67%	-3.33%	-7.98%	-12.44%	-18.10%	4.70%	12.16%	29.83%
		Change	0.00%	0.39%	2.36%	3.34%	7.72%	**-6.93%**	0.00%	**-3.46%**
KRTU	C180	kWh	15.768	11.325	25.253	10.896	24.364	35.24	31.987	154.83
	1s	kWh	33.067	18.297	28.283	21.904	36.579	45.79	39.524	223.44
	GLR	% Error	109.71%	61.56%	12.00%	101.03%	50.14%	29.94%	23.56%	44.31%
	MSR	kWh	32.439	17.889	25.475	21.904	36.563	45.790	39.524	219.58
	GLR	% Error	105.73%	57.96%	0.88%	101.03%	50.07%	29.94%	23.56%	41.82%
		Change	**-3.98%**	**-3.60%**	**-11.12%**	0.00%	-0.07%	0.00%	0.00%	**-2.49%**
Exhaust Fans	C180	kWh	7.941	7.879	8.307	2.472	7.759	11.47	10.371	56.20
	1s	kWh	10.570	12.856	9.881	6.161	15.293	19.151	22.781	96.69
	GLR	% Error	33.11%	63.17%	18.95%	149.23%	97.10%	66.97%	119.66%	72.05%
	MSR	kWh	13.223	12.856	15.508	9.161	15.293	19.151	22.781	107.97
	GLR	% Error	66.52%	63.17%	86.69%	270.59%	97.10%	66.97%	119.66%	92.12%
		Change	33.41%	0.00%	67.74%	121.36%	0.00%	0.00%	0.00%	20.07%
Oven	C180	kWh	6.984	6.672	7.398	1.986	6.628	8.52	7.128	45.32
	1s	kWh	7.427	6.873	6.527	1.896	6.490	9.3769	7.162	45.75
	GLR	% Error	6.34%	3.01%	-11.77%	-4.53%	-2.08%	10.06%	0.48%	0.95%
	MSR	kWh	7.310	6.782	6.623	1.896	6.565	9.300	7.067	45.54
	GLR	% Error	4.67%	1.65%	-10.48%	-4.53%	-0.95%	9.15%	-0.86%	0.49%
		Change	**-1.67%**	**-1.36%**	**-1.29%**	0.00%	**-1.13%**	**-0.91%**	0.38%	**-0.46%**

Since the current event detection algorithm has a very good detection rate, it seems that the main cause for erroneous energy estimation is the misclassification of the detected events.

Improving Event Classification

Figure 4-24 shows an example depicting the qualitative effect of misclassification of events on the energy estimation. In the figure, the first and fourth rows represent the operation of the freezer coil defroster and icemaker, respectively, during an eight-hour period; the second and third rows represent the operation registered by the NILM system during the same period.

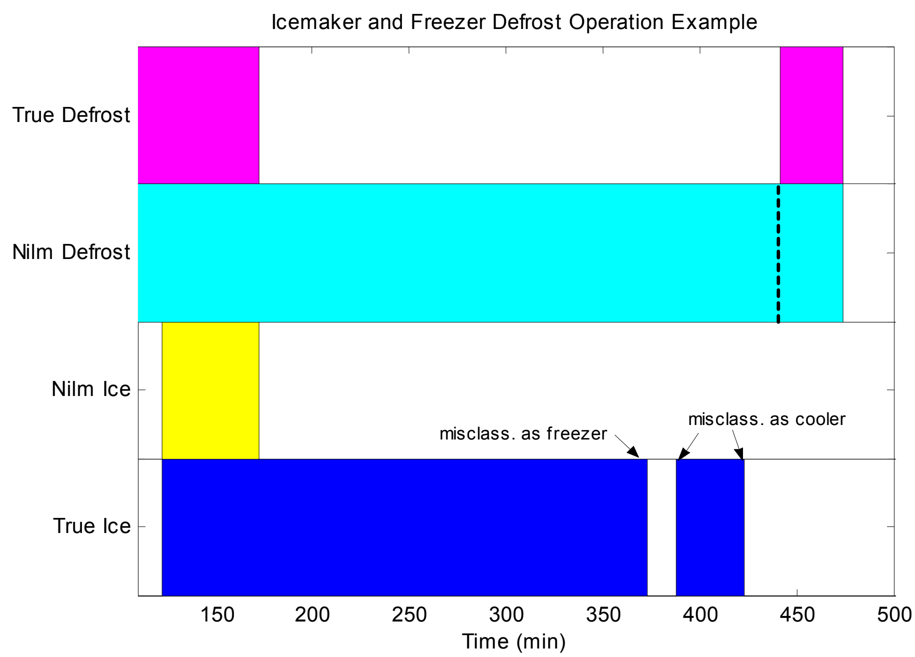


Figure 4-24 *Effect of Misclassification on Energy Estimation.*

The NILM correctly classified three of the four defroster events and only one of the four icemaker events in the sample period. Misclassifying the first defroster shutdown as an icemaker event caused an overestimation of the defroster's energy consumption, and an underestimation of the icemaker's energy consumption. The energy underestimation of the icemaker was made worse by the classification of the last three icemaker events as freezer and cooler events.

The misclassification of the icemaker, cooler and freezer events can be attributed primarily to the similarity of their steady state power consumption signatures. Figure 4-25 presents the power change database information corresponding to these loads.

In order to better distinguish between events whose steady-state power change would fall into one of the areas defined by the loads shown in Figure 4-25, an additional "dimension" or characteristic is needed besides the steady-state complex power consumption (two dimensions).

Table 11 presents the achievable energy estimation errors when all the events detected, when using the single-rate detection algorithm (1s GLR), are correctly classified, and compares them with the current steady-state NILM results. The energy values presented in the table were computed by feeding the energy estimation module with the correct classification of the single-load events[5], according to the information provided by the parallel metering system in the site.

Table 11 *Energy Estimation Errors with "Perfect" Classification of Detected Events.*

Device	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Week

[5] Events resulting from the simultaneous state change of two or more loads were not decomposed into their corresponding loads. The current NILM system implementation classifies these events as *non-identified* events.

Table 11 Energy Estimation Errors with "Perfect" Classification of Detected Events.

Device			Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Week
Icemaker	C180	kWh	8.006	6.429	5.945	4.658	10.193	8.85	6.993	51.07
	SS	kWh	6.407	2.802	10.816	2.529	6.247	10.193	11.41	50.40
	NILM	% Error	-19.97%	-56.42%	81.93%	-45.71%	-38.71%	15.18%	63.16%	-1.31%
	Mod.	kWh	7.929	6.359	6.583	4.700	10.141	8.846	6.867	51.43
	NILM	% Error	-0.96%	-1.09%	10.73%	0.90%	-0.51%	-0.05%	-1.80%	0.70%
		Change	-19.01%	-55.33%	-71.20%	-44.81%	-38.20%	-15.13%	-61.36%	-0.61%
Cooler	C180	kWh	16.227	14.352	12.078	7.781	12.271	18.66	22.823	104.19
	SS	kWh	14.998	17.869	12.499	8.443	13.014	20.945	25.573	113.34
	NILM	% Error	-7.57%	24.51%	3.49%	8.51%	6.05%	12.25%	12.05%	8.78%
	Mod.	kWh	16.327	14.780	12.161	7.626	12.155	19.777	21.326	104.15
	NILM	% Error	0.62%	2.98%	0.69%	-1.99%	-0.95%	5.99%	-6.56%	-0.04%
		Change	-6.95%	-21.53%	-2.80%	-6.52%	-5.10%	-6.26%	-5.49%	-8.74%
Freezer	C180	kWh	13.372	15.736	14.101	9.254	14.072	23.00	23.741	113.28
	SS	kWh	20.804	24.187	14.579	12.108	20.452	31.104	30.298	153.53
	NILM	% Error	55.58%	53.70%	3.39%	30.84%	45.34%	35.23%	27.62%	35.53%
	Mod.	kWh	14.456	17.021	12.627	8.642	12.292	19.082	27.878	112.00
	NILM	% Error	8.11%	8.17%	-10.45%	-6.61%	-12.65%	-17.03%	17.43%	-1.13%
		Change	-47.47%	-45.53%	7.06%	-24.23%	-32.69%	-18.20%	-10.19%	-34.40%
LRTU	C180	kWh	9.198	7.214	12.099	5.822	10.347	6.57	11.708	62.96
	SS	kWh	30.047	7.426	11.419	5.292	9.273	7.334	13.132	83.92
	NILM	% Error	226.67%	2.94%	-5.62%	-9.10%	-10.38%	11.63%	12.16%	33.29%
	Mod.	kWh	8.310	6.454	11.006	5.098	9.301	7.247	10.298	57.71
	NILM	% Error	-9.65%	-10.54%	-9.03%	-12.44%	-10.11%	10.30%	-12.04%	-8.34%
		Change	-217.02%	7.60%	3.41%	3.34%	-0.27%	-1.33%	-0.12%	-24.95%
KRTU	C180	kWh	15.768	11.325	25.253	10.896	24.364	35.24	31.987	154.83
	SS	kWh	33.067	18.297	28.283	21.904	36.579	45.79	39.524	223.44
	NILM	% Error	109.71%	61.56%	12.00%	101.03%	50.14%	29.94%	23.56%	44.31%
	Mod.	kWh	7.988	11.210	28.594	12.632	28.599	19.903	28.855	137.78
	NILM	% Error	-49.34%	-1.02%	13.23%	15.93%	17.38%	-43.52%	-9.79%	-11.01%
		Change	-60.37%	-60.54%	1.23%	-85.10%	-32.76%	13.58%	-13.77%	-33.30%
Exhaust Fans	C180	kWh	7.941	7.879	8.307	2.472	7.759	11.47	10.371	56.20
	SS	kWh	10.570	12.856	9.881	6.161	15.293	19.151	22.781	96.69
	NILM	% Error	33.11%	63.17%	18.95%	149.23%	97.10%	66.97%	119.66%	72.05%
	Mod.	kWh	9.047	9.049	9.047	2.7	8.833	13.335	6.93	58.94
	NILM	% Error	13.93%	14.85%	8.91%	9.22%	13.84%	16.26%	-33.18%	4.88%
		Change	-19.18%	-48.32%	-10.04%	-140.01%	-83.26%	-50.71%	-86.48%	-67.17%
Oven	C180	kWh	6.984	6.672	7.398	1.986	6.628	8.52	7.128	45.32
	SS	kWh	7.427	6.873	6.527	1.896	6.490	9.3769	7.162	45.75
	NILM	% Error	6.34%	3.01%	-11.77%	-4.53%	-2.08%	10.06%	0.48%	0.95%
	Mod.	kWh	7.404	6.873	7.48	1.926	6.507	9.286	7.15	46.63
	NILM	% Error	6.01%	3.01%	1.11%	-3.02%	-1.83%	8.99%	0.31%	2.89%
		Change	-0.33%	0.00%	-10.66%	-1.51%	-0.25%	-1.07%	-0.17%	1.94%

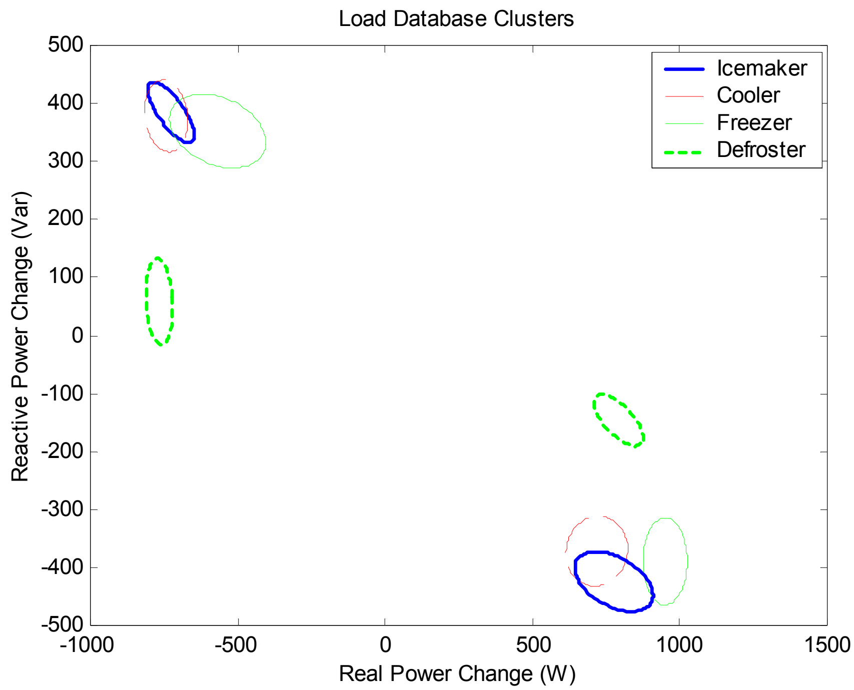


Figure 4-25 *Overlapping Load Database Clusters.*

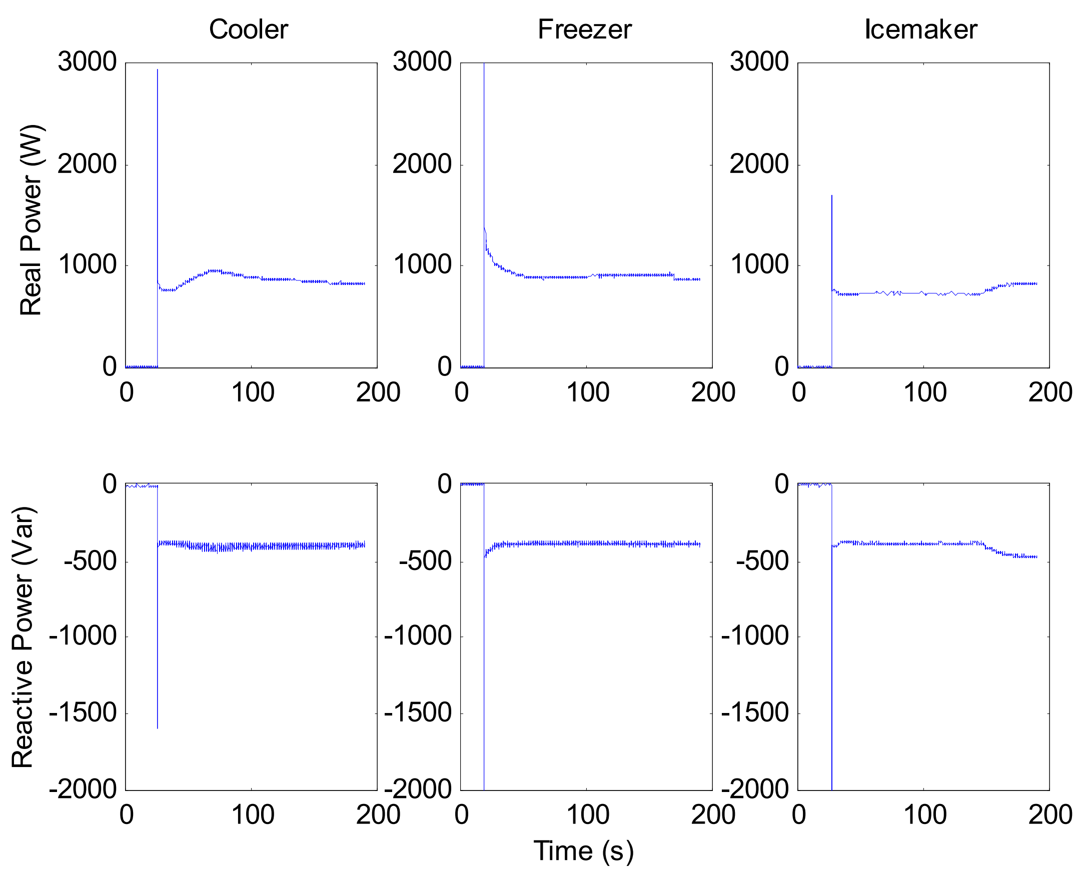


Figure 4-26 *Cooler, Freezer and Icemaker Transient Signatures.*

The energy estimation errors obtained when using the "perfect" event classification are mainly due to missing load events due to the either non-detection (the fewer) and composite events that were not identified. Composite events are events resulting from the simultaneous, or almost simultaneous, state change of multiple loads, and algorithms to deal with them are being studied and developed. Additionally, two methods to complement, or supplement, the steady-state classification process are being currently studied in order to achieve "perfect" classification of the detected events. The first method uses transient signatures during the classification process, while the second method uses building information in addition to the measured power.

Using Transient Signatures

Transient signatures are being investigated as a mean to distinguish between loads that have similar steady-state power change signatures. For example, the power waveforms generated by the cooler, freezer and icemaker operation present distinct transient shapes (Figure 4-26), and therefore their transient characteristics might be used as the additional "dimension" or characteristic needed to disaggregate these loads correctly.

The turn-on and shutdown transient patterns information (also referred to as *exemplars*) for the loads in the monitored circuit are extracted from the data collected at the site and incorporated into the load database, and the NILM software modified to use the *exemplars* in the classification process.

The steady-state NILM system with transient identification currently being developed differs from previously developed transient based NILM systems (Leeb and Shaw [3,4,12]), in that the transient identification process is a complement to the steady-state classification process. Transient signatures are used in the classification process only when the steady-state signatures are not sufficient to associate a particular event to a single load with enough certainty. When an event can be associated to various loads based on the steady-state signature alone, the *exemplars* for the possible loads are be retrieved from the load database and compared to the transient shape of the event. The event is associated to the load whose *exemplar* best matches the event transient.

Using the transient classification process on a need basis only, and with a varying subset of the *exemplar* load database, would improve the classification process by using the positive attributes of transient classification while reducing the effect of its disadvantages, such as the increased computational cost and noise sensitivity.

Using Building Information

An alternative to transient identification for disaggregating loads with similar steady state characteristics would be to use building information. The building information could be obtained from a building energy management system (BEMS) or from the equipment controllers. It could also be obtained from equipment operation schedules, models, or system design intent.

Having control signals, or similar information from the operation of the equipment is important for event classification, as well as for fault detection. For example, the presence of a control signal from the BEMS (or its absence) could be used to verify the classification of a NILM observed event. It could also indicate the existence of a fault when the observed event does not correspond to the issued control signal.

4.4 NILM Report Generation

The current implementation of the NILM system distributes the software modules between the remote computer, installed at the monitored site, and a "central" computer, which processes the data obtained from the remote site offline.

The block diagram of the current NILM software implementation is shown in Figure 4-27 (the figure is similar to the one presented in Figure 2-3). This diagram shows the current distribution of the modules among the remote and "central" computers, as well as the information shared between the modules. Since most of the NILM software resides currently in the "central" computer, all the information generated by the system is readily available and obtained by directly accessing the system variables shown in Figure 4-27.

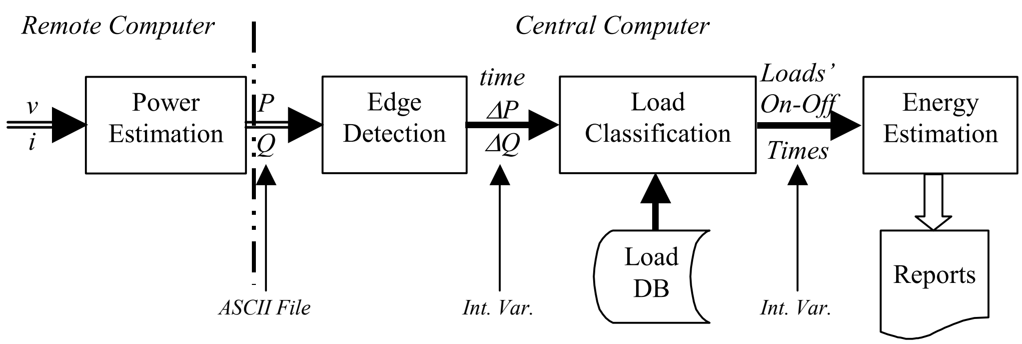


Figure 4-27 *Current NILM Software Architecture Block Diagram.*

However the intended role of the "central" computer is not the analysis of the NILM data, but rather the management of different monitoring computers and the site information obtained from them. Each of the remote computers would host the NILM software in its entirety and would provide the relevant site information to the "central" computer in the form of report files transmitted using the Internet or a modem connection.

Two reports, in ASCII format, can then be generated for each site monitored by the central computer. The first report presents energy consumption information for the whole site and the individual loads identified in the site. This information includes:

1) Total energy consumption in kWh.
2) Average power consumption per hour in W.

A sample of the energy-consumption report generated by the NILM software is presented in Figure 4-28. The sample report presented was obtained from 25 hours of data. Total energy consumption values shown correspond to the energy consumed during the whole recorded period. Average power consumption values shown correspond only to the first three hours of the recorded period.

In addition to the text file provided, average power use data can be plotted to show at a glance energy consumption trends, for the total building or individual loads.

```
DATA FROM FILE: t20001212
2000.12.12 18:45
2000.12.13 19:48

* Total Energy Consumption (kWh)

Total   Ice    Cooler Freez1 Freez2 LRTU1  LRTU2   KRTU1  KRTU2 KRTUs  Exh1  Exh2   Oven
95.773  10.816 4.767  11.991 1.679  11.134 0.000   23.932 4.350 0.000  9.139 0.742  6.527

* Average Power Use per Hour (W)

Hour Total Ice    Cooler Freez1 Freez2 LRTU1  LRTU2  KRTU1  KRTU2  KRTUs  Exh1   Exh2  Oven
1    4266  0.0    0.0    509.9  0.0    524.8  0.0    1544.8 0.0    0.0    380.7  265.4 376.6
2    4137  0.0    281.3  102.1  163.1  550.2  0.0    1544.8 0.0    0.0    380.7  265.4 315.8
3    4630  0.0    342.7  640.7  256.3  744.2  0.0    590.5  0.0    0.0    380.7  211.3 303.6
```

***Figure 4-28** Energy-Consumption Report Sample.*

Figure 4-29 shows sample average power consumption plots extracted from the report file. The average power use for the whole building and the cooler are presented in the plots.

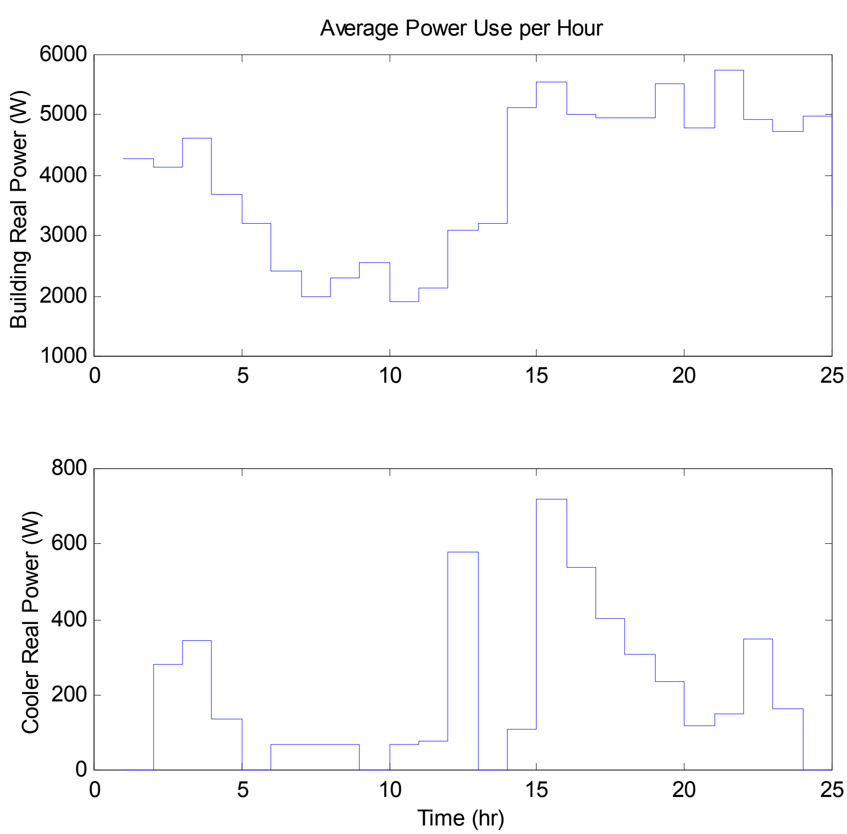


Figure 4-29 *Average Power Consumption Plots.*

The second report presents information on the operation of the different loads in the monitored site, such as the time of the events detected in hr:min:sec from the beginning of the reporting period and their classification. Figure 4-30 shows a sample of the event report for a period of 6 hours. The figure presents the whole site event classification, and the time of the events that were associated to the cooler.

```
DATA FROM FILE: t20001212
2000.12.12 22:45
2000.12.13 04:48

* Total Event List (* indicates conflict)

 Time     Event Name    Time     Event Name    Time     Event Name    Time     Event Name
00:00:21  LRTU1_Off    01:36:41  Freez1_Off   03:24:17  Cooler_On    04:23:40  non ident.
00:05:47  Ice_On       01:40:22  LRTU1_Off    03:25:03  LRTU1_On     04:26:50  LRTU1_On
00:09:07  Ice_On*      01:50:04  LRTU1_On     03:29:52  Cooler_Off   04:33:00  KRTU1_Off
00:11:03  LRTU1_On     01:55:50  LRTU1_Off    03:31:05  LRTU1_Off    04:42:10  LRTU1_On*
00:15:02  Cooler_Off*  02:02:38  Ice_On       03:35:11  Ice_On*      04:46:28  Ice_On*
00:16:33  LRTU1_Off    02:04:59  Freez1_On    03:35:36  Freez1_Off   04:48:24  LRTU1_Off
00:27:24  LRTU1_On     02:06:24  LRTU1_On     03:40:27  LRTU1_On     04:52:04  Cooler_Off*
00:32:09  LRTU1_Off    02:08:24  Cooler_Off*  03:46:18  Freez2_On    04:57:18  LRTU1_On
00:37:37  Freez1_Off*  02:12:10  LRTU1_Off    03:46:33  LRTU1_Off    05:03:32  LRTU1_Off
00:43:28  LRTU1_On     02:22:20  LRTU1_On     03:47:49  Freez1_On    05:05:53  LRTU2_Off*
00:45:34  Ice_On*      02:28:14  LRTU1_Off    03:48:06  Freez1_Off   05:12:30  LRTU1_On
00:48:49  LRTU1_Off    02:36:17  Freez1_Off   03:56:07  LRTU1_On     05:18:43  LRTU1_Off
00:51:22  Ice_Off      02:38:12  LRTU1_On     04:00:34  Ice_On*      05:27:46  LRTU1_On
01:00:56  LRTU1_On     02:43:27  Cooler_On    04:02:08  LRTU1_Off    05:28:54  Cooler_On
01:05:49  LRTU1_Off    02:44:05  LRTU1_Off    04:06:54  Cooler_Off*  05:32:18  Freez1_On*
01:05:56  Freez1_On    02:49:02  Cooler_Off   04:09:03  Freez1_Off*  05:34:03  LRTU1_Off
01:17:08  LRTU1_On     02:53:48  LRTU1_On     04:11:35  LRTU1_On     05:34:24  Cooler_Off
01:22:17  LRTU1_Off    02:59:49  LRTU1_Off    04:17:36  LRTU1_Off    05:43:06  LRTU1_On
01:22:39  LRTU1_Off*   03:06:14  Freez1_On    04:18:10  Freez2_Off   05:49:27  LRTU1_Off
01:23:32  Cooler_On    03:09:32  LRTU1_On     04:18:14  Freez1_On    05:54:17  KRTU2_Off*
01:29:23  Cooler_Off   03:15:33  LRTU1_Off    04:22:25  non ident.   05:58:21  LRTU1_On

* Event List by Load (* means conflict)

Events Registered for Cooler.

 Time     Event      Time     Event      Time      Event      Time       Event
00:15:02  Off*     02:08:24  Off*     03:24:17  On        04:52:04   Off*
01:23:32  On       02:43:27  On       03:29:52  Off       05:28:54   On
01:29:23  Off      02:49:02  Off      04:06:54  Off*      05:34:24   Off
```

Figure 4-30 *Event Report Sample.*

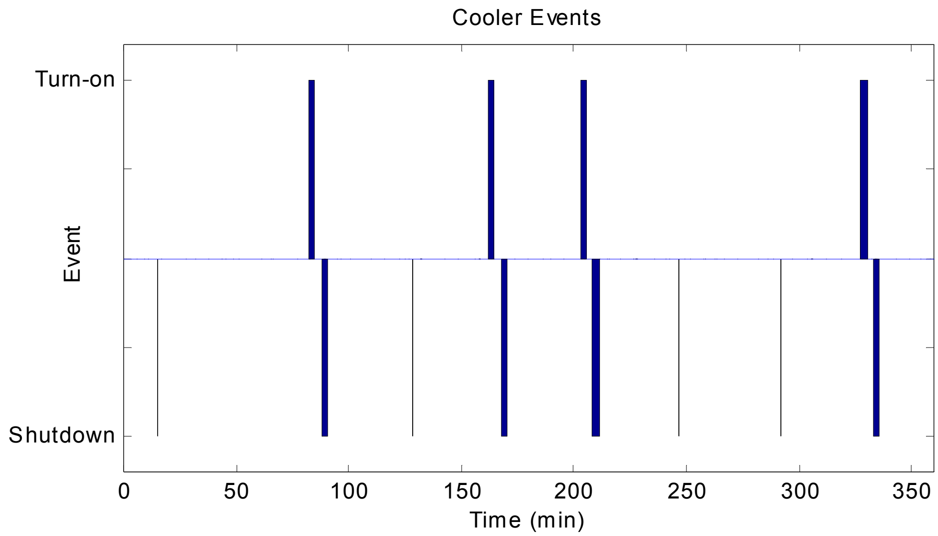


Figure 4-31 *Cooler Events Plot Sample.*

In addition to the information described, each report contains a header with general site and time information, such as site name, date, and start and end time of data reported. Figure 4-31 shows a plot extracted from the information contained in the event report. The bars represent the cooler events, turn-on and shutdown, with the thinner bars in the figure indicating events that caused a conflict with the previous load state.

5 Conclusions

A steady-state Non Intrusive Load Monitor (NILM) system developed at MIT was installed at KFC Restaurant in Norwell, Massachusetts. The NILM system monitored one phase of the electrical panel servicing the mechanical equipment of the restaurant. The equipment monitored consisted of two multi-stage HVAC roof top units, two refrigeration units, three ventilation units (exhaust and make-up fans), an icemaker machine and a convection oven.

In addition of the NILM system, a commercial sub-metering and logging system (Synergistic C180 system) was installed to compare and validate the results obtained from the NILM system.

The NILM hardware installed at the site consists of a compact personal computer with a data acquisition (DAQ) board and a network interface card. Voltage and current measurements are taken via voltage taps and solid core current transducers and interfaced with the DAQ board through signal conditioning hardware. A DSL Internet connection was installed at the site to provide remote access to the computer. The computer runs Linux as operating system.

The NILM software is divided into five modules, each performing a specific task of the steady state NILM algorithm. These tasks are power preprocessing, event detection, event classification, energy use estimation, and report generation. The first module resides in the on-site computer while the remaining modules are implemented using Matlab® in a remote and off-line computer.

Reports generated by the NILM system provide information on the energy consumption and time of use activity of the different loads in the building.

5.1 Power Measurement Module

The power measurement module uses the current and voltage measurements to estimate the circuit power consumption. The algorithm used is known as the power spectral envelope processor and it estimates the fundamental and harmonic components of real and reactive power.

This software module operates in the on-site computer. The resulting data (real and reactive power) are stored in the computer hard disk until its retrieval using the network connection.

5.2 Event Detection Module

Changes in steady-state power consumption above a specified threshold are defined as events. A positive change in steady state real power use is considered a turn-on event while a negative change in steady state real power use is considered a shutdown event. These events are generated by the turn-on and shutdown respectively of loads in the monitored circuit.

The Generalized Likelihood Ratio (GLR) algorithm is used to detect events using the power data generated by the power spectrum envelope module. When an event is detected, the time of its occurrence, as well as its associated steady-state power change (real and reactive) are stored.

The event detection module is implemented using Matlab® in an off-line computer. It achieved an event detection rate of 97.4%.

Errors by the event detection algorithm can be classified as false alarm errors and missed event errors. The first type reports the occurrence of "non-existing" events, while the second type is the omission of events. Omitted events are the result of simultaneous events or closely spaced events (overlapping). Noise and load variations, other than "on" or "off" events, are the causes for false alarms.

A multi-sampling rate GLR algorithm was tested on the collected data in order to obtain better detection rates with the goal of obtaining better energy estimates. The multi-sampling rate GLR did achieved a better detection rate than the single rate GLR, however at higher memory and computational expense. Furthermore, the difference in the energy estimation results between the two detection methods did not warrant the additional cost and complexity of the multi-sampling rate GLR.

5.3 Event Classification Module

Events are classified as belonging to a load class based on their steady state real and reactive power changes. A database containing information on the loads' steady state real and reactive power change values was manually created using experimental data from the site, and is used by the event classification module.

The load database information defines elliptical areas (or clusters) in the complex power space for each load event (turn-on and shutdown). The distances of an event in the complex power space from the elliptical areas are used to define its membership (or lack of it) to one of the load clusters. The load database also contains information on the average power consumption of the load during its "on" and "off" states.

The event classification module had a correct classification rate of 91.4% from all detected events. However, when the oven events were removed from the selection set, the correct event classification rate was 88.4%. Loads generating a higher number of events during the recording period were identified correctly at higher rates than loads generating lower number of events.

Loads presenting similar steady-state power change values were one of the principal causes for misclassification errors. The walk-in cooler and icemaker presented similar steady state signatures (their clusters overlap severely), and generated most of the classification errors. Overlapping and simultaneous events also generated classification errors, since there are assimilated into a single composite event. The composite signatures were not included in the load database used, as their inclusion in the database is impractical. Methods need to be developed to address the issue of composite events.

Other classification methods are needed to accurately disaggregate the loads that present similar steady state signatures. A possible method currently under investigation is the use of transient signatures in conjunction with steady state signatures for classification. Another method to improve classification involves using building information, such as equipment control signals and operation schedules, during the classification process.

5.4 Energy Estimation Module

The energy estimation module computes the total energy used by the monitored circuit as well as energy used by individual loads. Total energy is estimated using the data obtained from the power measurement module. Energy use by the different loads is estimated using the information on the load events from the event classification module and the load average power consumptions contained in the load database. The energy estimation is highly dependent on the correct detection and classification of the load events, as well as the power consumptions values contained in the load database.

The energy consumption estimates for the loads were found to depend on their activity rates. Loads with few events during the day (or recording period) had large energy estimation errors when compared to the energy estimated reported by the parallel metering system. Similarly loads with a large number of events had lower energy estimation errors. Loads with high activity rates, such as the oven and cooler, had estimation errors under 25%, while loads with low activity rates, such as the icemaker and some ventilation units, presented errors over 19% and as high as 250%. The dependence of the energy estimation on load activity is a result of its dependence on correct event identification.

Energy estimation within 12% for most of the loads and days of the values reported by the parallel metering system were achieved when a “perfect” classification of the detected events (performed manually) was used for the Energy Estimation Module instead of the classification results obtained from the Event Classification Module. The main cause of error in the energy estimation with “perfect” classification resulted from missed load events due to the simultaneous state change of multiple loads, which generated composite events that were not classified. Better energy estimation would be achieved when algorithms to decompose composite events into their individual load events are developed and implemented.

6 References

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Appendix A Report Generation

A.1 Energy Report File Example

DATA FROM FILE: t20001211
START TIME & DATE
END TIME & DATE

* Total Energy Consumption (kWh)

Total	Ice	Cooler	Freez1	Freez2	LRTU1	LRTU2	KRTU1	KRTU2	KRTUs	Exh1	Exh2	Oven
83.04	2.802	9.273	13.032	10.332	1.709	5.267	10.060	5.265	2.972	9.139	3.717	6.873

* Average Power Use per Hour (W)

Hour	Tota	Ice	Cooler	Freez1	Freez2	LRTU1	LRTU2	KRTU1	KRTU2	KRTUs	Exh1	Exh2	Oven
1	3461	0.0	596.7	245.0	0.0	0.0	588.6	1544.8	226.0	115.7	380.7	265.4	45.3
2	3556	0.0	301.0	319.9	0.0	0.0	588.6	1544.8	0.0	115.7	380.7	265.4	547.3
3	4383	616.4	99.2	949.5	0.0	0.0	588.6	1544.8	169.3	118.9	380.7	265.4	368.6
4	4113	563.1	353.5	949.5	747.7	0.0	588.6	1544.8	24.0	115.7	380.7	265.4	191.4
5	3230	0.0	434.3	744.9	791.2	0.0	240.9	541.5	169.0	115.7	380.7	15.6	0.0
6	2153	0.0	371.1	764.1	791.2	0.0	0.0	0.0	0.0	56.3	380.7	0.0	0.0
7	2296	456.7	155.8	489.3	791.2	0.0	0.0	0.0	0.0	112.6	380.7	0.0	0.0
8	1660	0.0	131.3	549.4	791.2	0.0	0.0	0.0	0.0	56.3	380.7	0.0	0.0
9	1686	0.0	100.7	949.5	791.2	0.0	0.0	0.0	0.0	112.6	380.7	0.0	0.0
10	2108	54.7	113.3	455.8	462.6	0.0	0.0	0.0	0.0	118.9	380.7	0.0	0.0
11	2325	775.9	134.1	949.5	0.0	0.0	0.0	0.0	0.0	56.3	380.7	0.0	0.0
12	1743	335.1	485.4	560.5	0.0	0.0	0.0	0.0	71.6	115.7	380.7	0.0	0.0
13	2069	0.0	324.4	624.3	0.0	0.0	0.0	0.0	332.7	112.6	380.7	0.0	0.0
14	2080	0.0	718.2	614.6	0.0	0.0	0.0	0.0	388.2	56.3	380.7	0.0	0.0
15	4019	0.0	718.2	761.2	0.0	0.0	380.0	0.0	388.2	112.6	380.7	250.0	533.1
16	4862	0.0	718.2	7.1	747.0	0.0	588.6	0.0	388.2	59.4	380.7	265.4	593.5
17	5022	0.0	529.3	0.0	791.2	0.0	588.6	1.7	388.2	115.7	380.7	265.4	515.2
18	6091	0.0	700.0	611.1	791.2	0.0	588.6	197.4	388.2	115.7	380.7	265.4	665.1
19	5695	0.0	718.2	485.8	791.2	0.0	525.2	310.2	388.2	1188.8	380.7	265.4	746.7
20	3684	0.0	718.2	393.3	791.2	0.0	0.0	0.0	388.2	0.0	380.7	265.4	345.5

```
21     3430   0.0    341.9   475.3   791.2  0.0    0.0    19.7   388.2 0.0    380.7 265.4
       488.8
22     3971   0.0    180.7   451.3   463.1  396.6  0.0    4.3    388.2 0.0    380.7 265.4
       692.0
23     4488   0.0    181.3   366.9   0.0    769.3  0.0    1254.3 388.2 0.0    380.7 265.4
       474.2
24     4895   0.0    144.2   314.1   0.0    543.2  0.0    1544.8 388.2 0.0    380.7 265.4
       660.4
25     5123   0.0    718.2   0.0     0.0    0.0    0.0    1544.8 388.2 0.0    380.7 265.4
       1285.6
```

A.2 Event Report File Example

```
DATA FROM FILE: t20001213
START TIME & DATE
END TIME & DATE

* Total Event List (* indicates conflict)

 Time   Event Name       Time   Event Name       Time   Event Name       Time   Event
Name
00:00:34Oven_On         01:26:31Oven_Off        06:11:38LRTU1_Off       12:12:08
   Cooler_On
00:01:19Oven_Off        01:28:45non identified    06:12:12Freezer1_Off    12:17:41
   Cooler_Off
00:01:45Freezer1_Off*   01:29:24Oven_Off*       06:24:50LRTU1_On        12:21:43
   Exh1_On*
00:04:10Oven_On         01:31:40Oven_On         06:27:35Cooler_On       12:21:46
   Exh2_On
00:04:47Oven_Off        01:32:18Oven_Off        06:29:27LRTU1_Off       12:23:33
   Freezer1_On
00:05:16Cooler_On       01:34:12LRTU1_On*       06:31:54Cooler_On*      12:25:21
   LRTU1_On
00:06:29LRTU1_On        01:34:35Oven_On         06:33:12Freezer1_Off*   12:30:15
   LRTU1_Off
00:07:41Oven_On         01:35:15Oven_Off        06:37:43Cooler_Off      12:44:30
   LRTU1_On
00:08:18Oven_Off        01:35:37Cooler_Off*     06:42:18LRTU1_On        12:49:57
   Cooler_On
00:11:04Cooler_Off      01:37:35Oven_On         06:46:55LRTU1_Off       12:50:11
   LRTU1_Off
00:11:20Oven_On         01:38:14Oven_Off        06:52:56Freezer1_On     12:50:27
   Oven_On
00:11:56Oven_Off        01:40:34Oven_On         06:59:46LRTU1_On        12:52:31
   Exh2_Off
00:14:39LRTU1_Off       01:41:12Oven_Off        07:02:51Cooler_Off*     12:53:36Ice_On

00:14:59Oven_On         01:42:00Cooler_On       07:04:16LRTU1_Off       12:57:23
   Oven_Off
00:15:36Oven_Off        01:43:34Oven_On         07:10:05Cooler_On       12:57:46
   Oven_On
00:18:43Oven_On         01:43:42LRTU1_Off       07:15:43Cooler_Off      13:02:14
   LRTU1_On
00:19:19Oven_Off        01:44:12Oven_Off        07:16:10Freezer1_Off    13:03:52
   Cooler_On*
00:19:36Cooler_On       01:48:46Ice_Off         07:17:35LRTU1_On        13:07:55
   LRTU1_Off
00:20:45LRTU1_On        01:51:28LRTU1_On        07:21:34Freezer2_On*    13:08:24
   Oven_Off
```

00:22:17Oven_On	01:53:24Exh2_On*	07:22:12LRTU1_Off	13:09:08Oven_On
00:22:54Oven_Off	01:58:14LRTU1_Off	07:35:52LRTU1_On	13:12:02Oven_Off
00:25:51Oven_On	02:01:53Ice_On	07:40:29LRTU1_Off	13:12:46Oven_On
00:26:28Oven_Off	02:04:32LRTU1_On	07:42:05Cooler_On	13:14:25Oven_Off
00:28:11LRTU1_Off	02:13:09Cooler_On*	07:48:12Cooler_Off	13:15:15Oven_On
00:28:51Freezer1_On	02:13:42LRTU1_Off	07:53:23Freezer2_Off	13:16:42Oven_Off
00:29:30Oven_On	02:20:48LRTU1_On	07:53:26Freezer1_On	13:17:36Oven_On
00:30:07Oven_Off	02:21:41KRTU2_Off*	07:54:00LRTU1_On	13:18:57Oven_Off
00:33:07Oven_On	02:21:45Exh2_Off	07:58:41LRTU1_Off	13:19:53Oven_On
00:33:44Oven_Off	02:27:58LRTU1_Off	08:01:22non identified	13:19:58LRTU1_On
00:36:29LRTU1_On	02:34:36Cooler_Off	08:12:33LRTU1_On	13:21:11Oven_Off
00:36:47Oven_On	02:38:24LRTU1_On	08:17:14LRTU1_Off	13:21:36Freezer2_On
00:37:24Oven_Off	02:43:26LRTU1_Off	08:23:29Cooler_On	13:21:50Freezer1_Off
00:40:26Oven_On	02:52:07Ice_Off	08:29:14Cooler_Off	13:22:09Oven_On
00:41:03Oven_Off	02:54:16LRTU1_On	08:30:57LRTU1_On	13:23:24Oven_Off
00:42:23Freezer1_Off	02:58:01Cooler_On	08:35:42LRTU1_Off	13:24:24Oven_On
00:44:04Oven_On	02:59:06LRTU1_Off	08:49:13LRTU1_On	13:25:36Oven_Off
00:44:07LRTU1_Off	03:04:27Cooler_Off	08:50:13Freezer1_Off	13:25:55LRTU1_Off
00:44:40Oven_Off	03:10:49LRTU1_On	08:53:55LRTU1_Off	13:26:37Oven_On
00:47:42Oven_On	03:13:17Freezer1_On	09:02:28Cooler_On	13:27:47Oven_Off
00:48:19Oven_Off	03:15:34LRTU1_Off	09:07:22LRTU1_On	13:28:51Oven_On
00:50:12LRTU1_On	03:27:45LRTU1_On	09:08:03Cooler_Off	13:29:49Oven_Off
00:51:13Oven_On	03:31:19Cooler_On	09:12:03LRTU1_Off	13:30:01Oven_On
00:52:45Oven_Off	03:32:26LRTU1_Off	09:12:33Freezer1_On	13:30:10Ice_Off
00:54:05Oven_On	03:37:30Ice_Off*	09:25:22LRTU1_On	13:30:51Oven_Off
00:54:58Oven_Off	03:38:30Freezer1_Off	09:30:07LRTU1_Off	13:31:46Oven_On
00:56:27Oven_On	03:44:42LRTU1_On	09:38:50Freezer1_Off	13:32:51Oven_Off
00:57:15Oven_Off	03:49:27LRTU1_Off	09:42:05Cooler_On	13:32:58Oven_On
00:57:35Cooler_Off	04:00:47Freezer1_On	09:43:54LRTU1_On	13:33:08Oven_Off
00:58:15LRTU1_Off	04:02:10LRTU1_On	09:47:43Cooler_Off	13:34:19Oven_On
00:58:20Freezer1_On	04:06:02Freezer1_On*	09:48:35LRTU1_Off	13:35:14Oven_Off

00:58:52Oven_On 04:06:47LRTU1_Off 09:59:47Freezer1_On 13:35:25
LRTU1_On
00:59:39Oven_Off 04:11:49Cooler_Off 10:02:46LRTU1_On 13:36:36
Oven_On
01:01:21Oven_On 04:19:54LRTU1_On 10:07:23LRTU1_Off 13:37:29
Oven_Off
01:02:06Oven_Off 04:24:10KRTU2_Off* 10:20:13Cooler_On 13:39:03
Oven_On
01:03:52Oven_On 04:24:27LRTU1_Off 10:21:18LRTU1_On 13:39:47
Oven_Off
01:04:36Oven_Off 04:37:47LRTU1_On 10:24:07Freezer1_Off 13:41:42
LRTU1_Off
01:05:36LRTU1_On 04:40:42Cooler_On 10:25:43Cooler_Off 13:41:45
Oven_On
01:06:29Oven_On 04:42:20LRTU1_Off 10:25:47LRTU1_Off 13:42:27
Oven_Off
01:07:11Oven_Off 04:44:55Freezer1_On* 10:39:46LRTU1_On 13:44:33
Oven_On
01:09:07Oven_On 04:46:31Cooler_Off 10:44:27LRTU1_Off 13:45:14
Oven_Off
01:09:49Oven_Off 04:52:36LRTU1_Off* 10:44:44Freezer1_On 13:47:12
Oven_On
01:11:49Oven_On 04:56:07LRTU1_On 10:52:44KRTU1_On* 13:48:18
Oven_Off
01:12:30Oven_Off 05:00:52LRTU1_Off 10:58:02Cooler_On 13:48:28
Oven_On
01:12:34Cooler_On 05:07:49Freezer1_Off 10:59:15LRTU1_On 13:50:44
LRTU1_On
01:13:50LRTU1_Off 05:13:44LRTU1_On 11:03:33Cooler_Off 13:50:58
Oven_Off
01:14:35Oven_On 05:16:43Cooler_On 11:03:40LRTU1_Off 13:51:53
Oven_On
01:15:15Oven_Off 05:18:29LRTU1_Off 11:11:51Freezer1_Off 13:53:06
Oven_Off
01:17:22Oven_On 05:22:31Cooler_Off 11:20:39LRTU1_On 13:54:05non
identified
01:18:02Oven_Off 05:27:24Freezer1_On 11:24:40LRTU1_Off 13:55:07
Oven_Off*
01:19:36Cooler_Off 05:31:20LRTU1_On 11:34:45Freezer1_On 13:56:18
Oven_On
01:20:10Oven_On 05:36:09LRTU1_Off 11:35:20Cooler_On 13:57:06
LRTU1_Off
01:20:50Oven_Off 05:49:09LRTU1_On 11:40:53Cooler_Off 13:57:19
Oven_Off
01:20:56LRTU1_On 05:50:18Freezer1_Off 11:41:08LRTU1_On 13:58:34
Oven_On
01:21:33Freezer2_On 05:53:54LRTU1_Off 11:44:53LRTU1_Off 13:59:32
Oven_Off
01:21:51Freezer1_Off 05:54:04Cooler_On 12:02:09Freezer1_Off 14:00:51
Oven_On
01:23:00Oven_On 05:59:52Cooler_Off 12:04:05LRTU1_On 14:01:28
Oven_Off
01:23:40Oven_Off 06:07:01LRTU1_On 12:08:06LRTU1_Off 14:03:32non
identified
01:26:31Oven_On 06:10:09Freezer1_On

* Event List by Load (* means conflict)

Events Registered for Ice.

Time	Event	Time	Event	Time	Event	Time	Event
01:48:46	Off	02:52:07	Off	12:53:36	On	13:30:10	Off
02:01:53	On	03:37:30	Off*				

Events Registered for Cooler.

Time	Event	Time	Event	Time	Event	Time	Event
00:05:16	On	03:04:27	Off	06:37:43	Off	09:47:43	Off
00:11:04	Off	03:31:19	On	07:02:51	Off*	10:20:13	On
00:19:36	On	04:11:49	Off	07:10:05	On	10:25:43	Off
00:57:35	Off	04:40:42	On	07:15:43	Off	10:58:02	On
01:12:34	On	04:46:31	Off	07:42:05	On	11:03:33	Off
01:19:36	Off	05:16:43	On	07:48:12	Off	11:35:20	On
01:35:37	Off*	05:22:31	Off	08:23:29	On	11:40:53	Off
01:42:00	On	05:54:04	On	08:29:14	Off	12:12:08	On
02:13:09	On*	05:59:52	Off	09:02:28	On	12:17:41	Off
02:34:36	Off	06:27:35	On	09:08:03	Off	12:49:57	On
02:58:01	On	06:31:54	On*	09:42:05	On	13:03:52	On*

Events Registered for Freezer1.

Time	Event	Time	Event	Time	Event	Time	Event
00:01:45	Off*	04:06:02	On*	06:52:56	On	10:24:07	Off
00:28:51	On	04:44:55	On*	07:16:10	Off	10:44:44	On
00:42:23	Off	05:07:49	Off	07:53:26	On	11:11:51	Off
00:58:20	On	05:27:24	On	08:50:13	Off	11:34:45	On
01:21:51	Off	05:50:18	Off	09:12:33	On	12:02:09	Off
03:13:17	On	06:10:09	On	09:38:50	Off	12:23:33	On
03:38:30	Off	06:12:12	Off	09:59:47	On	13:21:50	Off
04:00:47	On	06:33:12	Off*				

Events Registered for Freezer2.

Time	Event	Time	Event	Time	Event	Time	Event
01:21:33	On	07:21:34	On*	07:53:23	Off	13:21:36	On

Events Registered for LRTU1.

Time	Event	Time	Event	Time	Event	Time	Event
00:06:29	On	03:15:34	Off	06:42:18	On	10:21:18	On
00:14:39	Off	03:27:45	On	06:46:55	Off	10:25:47	Off
00:20:45	On	03:32:26	Off	06:59:46	On	10:39:46	On
00:28:11	Off	03:44:42	On	07:04:16	Off	10:44:27	Off
00:36:29	On	03:49:27	Off	07:17:35	On	10:59:15	On
00:44:07	Off	04:02:10	On	07:22:12	Off	11:03:40	Off
00:50:12	On	04:06:47	Off	07:35:52	On	11:20:39	On
00:58:15	Off	04:19:54	On	07:40:29	Off	11:24:40	Off
01:05:36	On	04:24:27	Off	07:54:00	On	11:41:08	On
01:13:50	Off	04:37:47	On	07:58:41	Off	11:44:53	Off
01:20:56	On	04:42:20	Off	08:12:33	On	12:04:05	On
01:34:12	On*	04:52:36	Off*	08:17:14	Off	12:08:06	Off
01:43:42	Off	04:56:07	On	08:30:57	On	12:25:21	On
01:51:28	On	05:00:52	Off	08:35:42	Off	12:30:15	Off
01:58:14	Off	05:13:44	On	08:49:13	On	12:44:30	On
02:04:32	On	05:18:29	Off	08:53:55	Off	12:50:11	Off
02:13:42	Off	05:31:20	On	09:07:22	On	13:02:14	On
02:20:48	On	05:36:09	Off	09:12:03	Off	13:07:55	Off
02:27:58	Off	05:49:09	On	09:25:22	On	13:19:58	On
02:38:24	On	05:53:54	Off	09:30:07	Off	13:25:55	Off
02:43:26	Off	06:07:01	On	09:43:54	On	13:35:25	On
02:54:16	On	06:11:38	Off	09:48:35	Off	13:41:42	Off
02:59:06	Off	06:24:50	On	10:02:46	On	13:50:44	On
03:10:49	On	06:29:27	Off	10:07:23	Off	13:57:06	Off

Events Registered for LRTU2.

No Events Registered

Events Registered for KRTU1.

Time	Event	Time	Event	Time	Event	Time	Event
10:52:44	On*						

Events Registered for KRTU2.

Time	Event	Time	Event	Time	Event	Time	Event
02:21:41	Off*	04:24:10	Off*				

Events Registered for KRTUs.

No Events Registered

Events Registered for Exh1.

Time	Event	Time	Event	Time	Event	Time	Event
12:21:43	On*						

Events Registered for Exh2.

Time	Event	Time	Event	Time	Event	Time	Event
01:53:24	On*	02:21:45	Off	12:21:46	On	12:52:31	Off

Events Registered for Oven.

Time	Event	Time	Event	Time	Event	Time	Event
00:00:34	On	00:54:05	On	01:35:15	Off	13:30:01	On
00:01:19	Off	00:54:58	Off	01:37:35	On	13:30:51	Off
00:04:10	On	00:56:27	On	01:38:14	Off	13:31:46	On
00:04:47	Off	00:57:15	Off	01:40:34	On	13:32:51	Off
00:07:41	On	00:58:52	On	01:41:12	Off	13:32:58	On
00:08:18	Off	00:59:39	Off	01:43:34	On	13:33:08	Off
00:11:20	On	01:01:21	On	01:44:12	Off	13:34:19	On
00:11:56	Off	01:02:06	Off	12:50:27	On	13:35:14	Off
00:14:59	On	01:03:52	On	12:57:23	Off	13:36:36	On
00:15:36	Off	01:04:36	Off	12:57:46	On	13:37:29	Off
00:18:43	On	01:06:29	On	13:08:24	Off	13:39:03	On
00:19:19	Off	01:07:11	Off	13:09:08	On	13:39:47	Off
00:22:17	On	01:09:07	On	13:12:02	Off	13:41:45	On
00:22:54	Off	01:09:49	Off	13:12:46	On	13:42:27	Off
00:25:51	On	01:11:49	On	13:14:25	Off	13:44:33	On
00:26:28	Off	01:12:30	Off	13:15:15	On	13:45:14	Off
00:29:30	On	01:14:35	On	13:16:42	Off	13:47:12	On
00:30:07	Off	01:15:15	Off	13:17:36	On	13:48:18	Off
00:33:07	On	01:17:22	On	13:18:57	Off	13:48:28	On
00:33:44	Off	01:18:02	Off	13:19:53	On	13:50:58	Off
00:36:47	On	01:20:10	On	13:21:11	Off	13:51:53	On
00:37:24	Off	01:20:50	Off	13:22:09	On	13:53:06	Off
00:40:26	On	01:23:00	On	13:23:24	Off	13:55:07	Off*
00:41:03	Off	01:23:40	Off	13:24:24	On	13:56:18	On
00:44:04	On	01:25:51	On	13:25:36	Off	13:57:19	Off
00:44:40	Off	01:26:31	Off	13:26:37	On	13:58:34	On
00:47:42	On	01:29:24	Off*	13:27:47	Off	13:59:32	Off
00:48:19	Off	01:31:40	On	13:28:51	On	14:00:51	On
00:51:13	On	01:32:18	Off	13:29:49	Off	14:01:28	Off
00:52:45	Off	01:34:35	On				

Events Registered for non identified.

Time	Event	Time	Event	Time	Event	Time	Event
01:28:45		08:01:22		13:54:05		14:03:32	

Appendix B Database Clusters Generation

B.1 Manual Cluster Parameter Computation

This section describes the method used to obtain the load's cluster information from the NILM data obtained during normal operation of the system. The process can be summarized in the following steps:

1) Event Detection. The Event Detection module is run on NILM power data to the events information, that is the times of the events and their corresponding real and reactive power changes.

2) Event Classification. The events obtained are manually classified as belonging to the different loads in the building using the parallel metering data. A Matlab® function displays the NILM and C180 data on a single window and allows the user to select the events believed to belong to the load of interest. Figure B-1 shows an example of the function's output while selecting the cooler events from a day data. Once the selection of the events, the function adds the position of the selected events to the *Event Matrix* generated by the Event Detection Module.

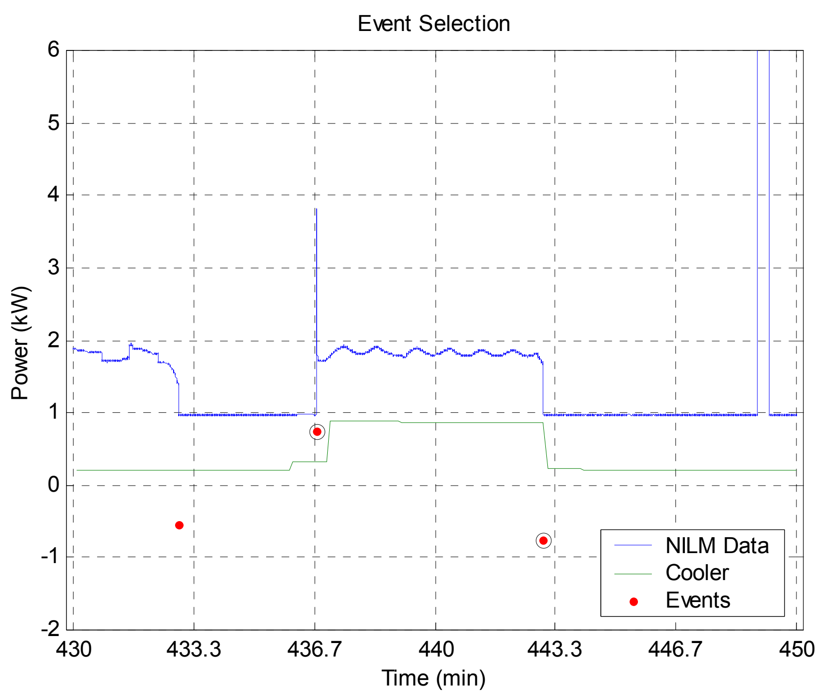

Figure B-1 *Cooler Event Selection.*

3) Cluster Selection. Using the information obtained from the event selection, the events selected are plotted in the complex power change plane. Another Matlab® function is used to manually group the points into clusters. The user defines rectangles containing the desired cluster points (Figure B-2) using the PC mouse.

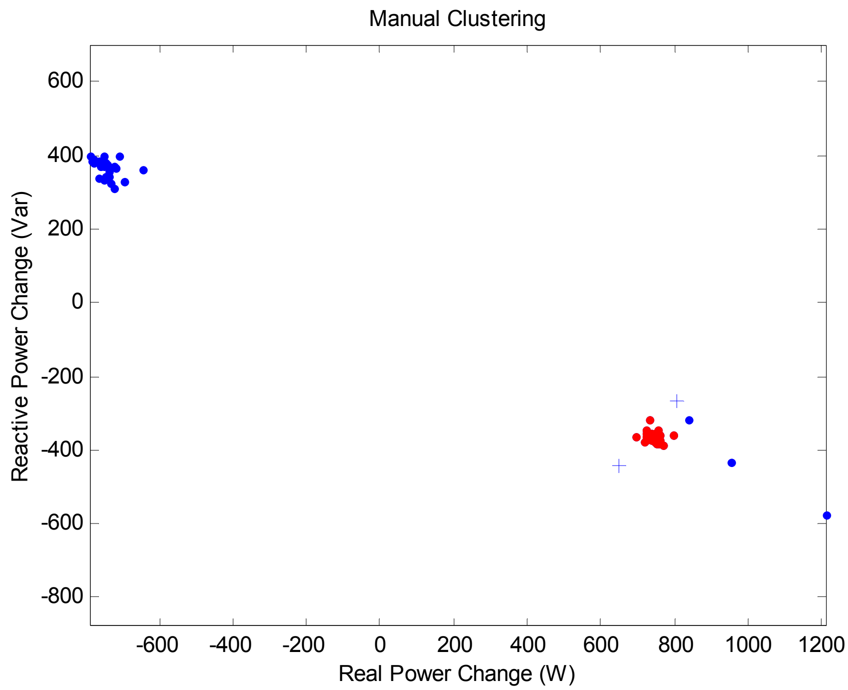

Figure B-2 *Manual Clustering of Cooler Events.*

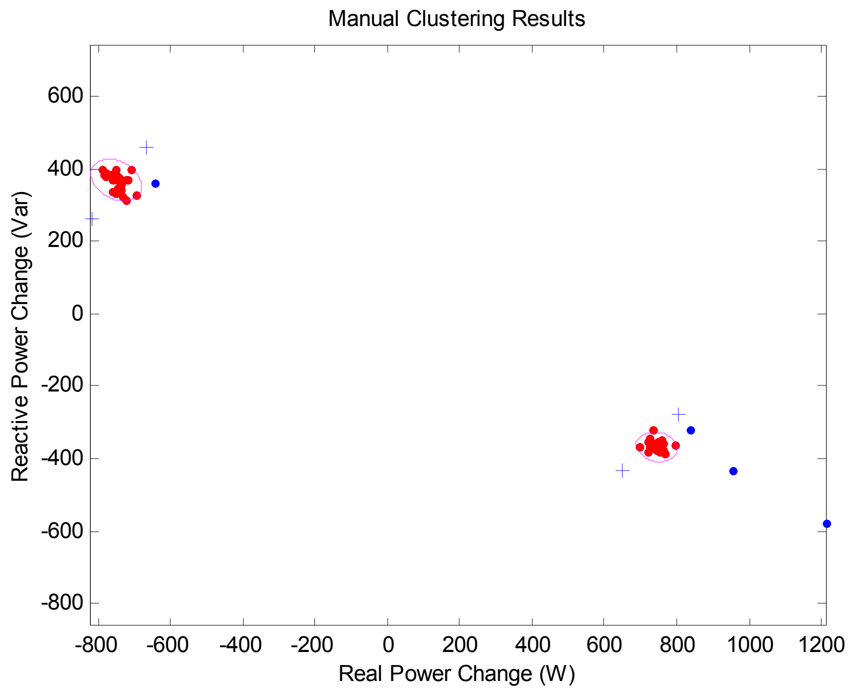

Figure B-3 *Clusters Resulting from Manual Selection.*

Once the user delimits the clusters, the function then computes the cluster statistical parameters (means, standard deviations and cluster angle) and plots the corresponding cluster ellipses (Figure B-3).